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Ex post impacts of improved maize varieties on poverty in rural Ethiopia

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Abstract

Public agricultural research has been conducted in Africa for decades. While many studies have examined its aggregate impacts, few have investigated how it affects the poor. This paper helps fill this gap by applying a new procedure to explore the *ex post* impacts of improved maize varieties on poverty in rural Ethiopia. Plot-level yield and cost changes due to adoption are first estimated using instrumental variable and marginal treatment effect techniques where possible heterogeneity is carefully accounted for. A backward derivation procedure is then developed to link treatment effect estimates with an economic surplus model to identify the counterfactual household income that would have existed without improved maize varieties. Poverty impacts are finally estimated by exploiting the differences between observed and counterfactual income distributions. Improved maize varieties have led to a 0.8–1.3 percentage drop of poverty headcount ratio and relative reductions of poverty depth and severity. However, poor producers benefit the least from adoption due to the smallness of their land holdings.

JEL classifications: I32, O33, Q16, Q18

Keywords: Improved maize varieties; Poverty; Impact; Ethiopia

1. Introduction

A major objective of crop genetic improvement (CGI) research is to generate new varieties to enhance the productivity or quality of food crops and reduce poverty (de Janvry and Sadoulet, 2002). According to the last comprehensive assessment completed more than a decade ago, CGI technologies have been available for many of the world's agro-ecologies and contributed to food production growth worldwide (Evenson and Gollin, 2003). In Sub-Saharan Africa (SSA), aggregate impacts of agricultural research have been well-documented (Norton and Alwang, forthcoming). There are, however, few studies of the poverty or other distributional impacts of improved crop varieties in SSA. Policy makers need information on these impacts to allocate resources to fruitful lines of research and to strengthen the role of agricultural research in poverty reduction.

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article.

Maize is among the most important food and cash crops in many environments in SSA. In Ethiopia, maize accounts for the largest share of production by volume and is produced by more farmers than any other crop (Chamberlin and Schmidt, 2012). From 1960s to 2009, the dietary calorie and protein contributions of maize in Ethiopia have doubled to around 20% and 16%, respectively (Shiferaw et al., 2013). In the last four decades, more than 40 improved maize varieties, including hybrids and open-pollinated varieties (OPVs), have been developed by the Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the International Maize and Wheat Improvement Center (CIMMYT). These varieties have been widely diffused through branches of the Ethiopian Seed Enterprise, the major seed producer and distributor, after rigorous on-farm verification, on-farm demonstration and pilot production. Despite their increasing importance, few studies have examined impacts of improved maize varieties in SSA beyond their impacts on productivity, profitability and basic economic surplus (Alene and Hassan, 2006; Seyoum et al., 1998).

This article bridges this gap using a new procedure to assess poverty impacts of CGI in Ethiopia. Using a recent household survey, we build this analysis from the plot-level to the household and the market. At the plot-level, the treatment effect

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estimates suggest a yield advantage of 47.6–63.3% for improved maize varieties over traditional varieties with 23.1–27.8% cost increase due to additional inputs. These estimates are incorporated into an economic surplus framework where changes in market prices and aggregate economic surplus are examined. The surplus changes are then apportioned back to producing and consuming households according to adoption status and maize consumption levels to examine how household well-being is affected. Poverty impacts are finally estimated as the differences between poverty indices computed using the observed and counterfactual income distributions. We find that improved maize varieties have led to a 0.8–1.3% reduction in the overall rural poverty headcount ratio, and proportional reductions in poverty depth and severity. However, poor producers are found to benefit the least from adoption because their land areas are relatively small.

2. Technology adoption and impact measurement

2.1. Direct and indirect effects of agricultural technology

Agricultural technology can reduce poverty through direct and indirect channels (de Janvry and Sadoulet, 2002). Direct benefits of improved crop varieties come from the yield advantages translated into reduced cost per unit of output, while indirect effects emerge at the market-level as prices may decline due to increased supply. These changes benefit consumers but adversely affect producers. Despite these confounding effects, CGI research is consistently linked to positive aggregate economic impacts in SSA (Alston et al., 2000; Alene and Coulibaly, 2009; Maredia et al., 2000; Renkow and Byerlee, 2010).

Assessments of market-level impacts usually employ partial equilibrium analysis such as economic surplus models and multi-market models (Alston et al., 1995; Karanja et al., 2003; Mills, 1997), or computable general equilibrium (CGE) analysis (de Janvry and Sadoulet, 2002). These market-level models, however, are not directly applicable for assessing impacts of CGI on the poor. To measure household-level indirect effects, a link is needed between market-level changes affecting producers and consumers and how these changes are distributed among households. Direct effects such as yield gains and additional costs are usually estimated using econometric modeling (Matuschke et al., 2007; Minten and Barrett, 2008; Suri, 2011), but distributional effects of market level changes are less frequently covered in this literature.

2.2. Treatment effects and agricultural technology impacts

Plot-level impacts of agricultural technology can be considered as treatment effects, where the treatment is technology adoption decision. Most treatment effect analyses using observational data are based on the potential outcomes framework (Rubin, 1974). Let T be a binary indicator of the treatment status (0 = not treated; 1 = treated), and y^T be the outcome of interest (e.g., crop yield). For each observed unit (e.g., land plot) the difference in average outcomes, or the naive average treatment effect estimate, can be expressed as (covariates suppressed):

$$\mathrm{E}(y^1|T=1)-\mathrm{E}(y^0|T=0)=\mathrm{E}(y^1-y^0|T=1) + [\mathrm{E}(y^0|T=1)-\mathrm{E}(y^0|T=0)]. \quad (1)$$

The right-hand side of Eq. (1) consists of two terms: the average treatment effect on the treated (ATT) and selection bias. The latter occurs in nonexperimental studies where the assignment of treatment (self-made decision to adopt technology) is nonrandom.

Strategies are needed to eliminate selection bias and identify the treatment effect under this endogeneity, with propensity score matching (Becerril and Abdulai, 2010; PSM; Kassie et al., 2011; Mendola, 2007) and instrumental variable (IV) techniques (Dercon et al., 2009; Matuschke et al., 2007; Minten and Barrett, 2008) among the most widely used. Both methods require specific assumptions to identify the treatment effect. PSM assumes that all determinants of selection into treatment are understood and observed. However, it can be violated as unobservable confounders such as farmer's motivation and risk attitude are likely to affect adoption and biased results may occur. Although there are methods to determine the degree of bias (Rosenbaum, 2002), there is no a priori reason to prefer PSM over the IV alternative. IV estimation implies assumptions about the correlations between treatment participation and outcomes. Suitable instruments are required that affect adoption but are uncorrelated with the outcome in other means. Although this assumption is not directly testable, concerns can be minimized if convincing IVs are found and well justified.

Possible differences in yield and cost changes across plots and households, or treatment effect heterogeneity, need to be carefully considered when measuring the direct impacts of technology adoption. Recent literature has yielded a number of promising approaches. For example, local average treatment effect (LATE) estimation (Imbens and Angrist, 1994) can be used to identify the treatment effect among compliers, whose probability of adoption is monotonically nondecreasing as they perceive the availability of the technology. Quantile IV regression (Chernozhukov and Hansen, 2005) can be used when heterogeneous impacts on different points of an outcome distribution are of interest. Marginal treatment effects (MTEs) reveal heterogeneous treatment effects across estimated propensity scores (Heckman et al., 2006). The MTEs can be aggregated to yield aggregate-level treatment effect parameters (average treatment effect, and that on the treated and untreated, respectively) via appropriate weighted averaging. While theoretical literature continues to grow, few empirical assessments of agricultural technologies have considered possible treatment effect heterogeneity.

3. Modeling procedure

3.1. Treatment effect estimation

Most empirical assessments of CGI impacts classify households as either adopters or nonadopters (Becerril and Abdulai, 2010; Kassie et al., 2011; Mendola, 2007). However, this classification does not identify partial adopters in our data, who adopt improved varieties only on some of their plots. Some studies model partial adoption as a rate or a continuum of land share. Empirical methods include the two-limit Tobit model where adoption rates are mapped on the double-censored unit interval (Lin, 1991), and the double hurdle model in which the decisions of whether and how much to adopt are assumed independent and sequential (Mal et al., 2012). Though suitable for modeling household-level adoption behavior, these methods cannot account for plot-level heterogeneity. As a result, we alternatively model adoption at the plot level as the maize variety on each plot, either improved or local varieties, is unique.

For each maize plot, the farm household expects a profit by selecting a maize variety on that plot, either improved ($T = 1$) or local ($T = 0$):

$$\mathrm{E}(\pi^T) = PY^T - C^T, \tag{2}$$

where Y^T and C^T represent the yield and input cost of maize variety T, and P is the maize market price. Ignoring risk, the plot-level adoption rule is written as:

$$T = \begin{cases} 1, & \text{if } \mathrm{E}(\pi^1) > \mathrm{E}(\pi^0) \\ 0, & \text{if } \mathrm{E}(\pi^1) \le \mathrm{E}(\pi^0) \end{cases} \tag{3}$$

On the production side, by specifying a suitable production function (e.g., Matuschke et al., 2007; Suri, 2011), the potential outcomes in terms of maize yield are specified in logarithmic form as:

$$\begin{aligned} y^1 &= \alpha^1 + \phi + X\beta^1 + u_y^1 \\ y^0 &= \alpha^0 + X\beta^0 + u_y^0 \end{aligned} \tag{4}$$

where φ is the plot-specific percentage yield gain with adoption; X is the input vector with coefficients β and u_y denotes unobservables. Equations (2)–(4) jointly specify the treatment effect model in linear form (Heckman et al., 2006). The production function can be compactly expressed as $y = Ty^1 + (1 - T)y^0$, or more specifically:

$$y = \alpha^0 + T(\alpha^1 - \alpha^0) + T\phi + X\beta^0 + TX(\beta^1 - \beta^0) + u \tag{5}$$

where $u = Tu_y^1 + (1 - T)u_y^0$. Estimation of Eq. (5) quantifies the yield advantage of improved maize varieties as the coefficient φ of the treatment indicator T. Notice that Eq. (5) allows for possible unobserved heterogeneity in the error term.

Changes in input costs associated with adoption, as farmers usually apply additional inputs in hope of fully realizing the yield advantages, can be estimated using a cost function approach, which is empirically specified as:

$$\begin{aligned} C^1 &= \lambda^1 + \theta + P\gamma^1 + u_C^1 \\ C^0 &= \lambda^0 + P\gamma^0 + u_C^0 \end{aligned} \tag{6}$$

In Eq. (6), C^T is the production cost of maize per hectare; P is a vector that includes input prices, plot area and the level of maize output and u_C denotes unobservables. Capital cost is not accounted for in the short-run analysis. Since $C = TC^1 + (1 - T)C^0$, the Generalized Roy Model can be expressed as:

$$C = \lambda^0 + T\left(\lambda^1 - \lambda^0\right) + T\theta + P\gamma^0 + TP\left(\gamma^1 - \gamma^0\right) + u_C \tag{7}$$

where $u_C = Tu_C^1 + (1 - T)u_C^0$. The parameter θ is interpreted as the plot-specific treatment effect in terms of percentage cost increase due to adoption.

Equations (5) and (7) are the main specifications for yield and cost ATT estimation. Since treatment is self-determined by farmers, IV techniques are used to account for potential endogeneity. Homogeneous treatment effects are assumed for baseline estimation. A simple 2SLS procedure is consistent, but may not fully capture the binary nature of the first-stage decision, and additional econometric techniques are implemented for robustness check purposes. One alternative we employ is to use the probit-estimate of the propensity score as the IV in the 2SLS procedure (probit-2SLS). This estimator is efficient and robust for misspecifications in the probit model (Wooldridge, 2002). To allow for arbitrary heteroskedasticity, Eq. (5) is also estimated using generalized method of moments (GMM, Hansen, 1982).

To account for possible variations of yield and cost treatment effects across plots and farm households, marginal treatment effects (MTEs) are estimated to allow for treatment effect heterogeneity (Heckman et al., 2006). The MTE provides treatment effect estimates at each propensity-score level, or the estimated probability of adoption. The MTE estimation is necessary since traditional IV and PSM techniques only provides mean ATT estimates and cannot account for heterogeneity across plots. Empirically, MTE estimation is carried out using a local instrumental variable (LIV) procedure where MTEs are estimated semiparametrically. With plot-specific MTEs obtained, an overall ATT can be derived by integrating out the observed characteristics which the MTEs are conditioned on (see appendix B in Heckman et al., 2006 for econometric details).

3.2. Indirect effects of technology adoption

To measure overall welfare effects of technology adoption, indirect effects need to be accounted for. These effects depend on the nature of the maize market. Two extreme cases are considered. In a small open economy, domestic maize market price is equal to the world price which does not change with increased domestic supply. Direct welfare effects occur only to adopters and no indirect effects occur. In a closed economy, indirect effects also occur due to supply-induced price drop and all market participants are affected. Specifically, consumers gain at the expense of producers, while adopters can still be better off if reductions in their per unit costs of production are large enough to offset negative price effects or if their maize sales are small. Ethiopia is not a member state of the World Trade Organization, where maize exports are occasionally restricted by cereal export bans for domestic food security. Thus, it can be considered a relatively closed economy for maize. However, cross-border trade still goes on even with cereal export bans. As a result, we assess poverty impacts of maize CGI in both cases, and the true poverty impacts will fall within the estimated bounds from these two cases.

In a small open economy, counterfactual household incomes are directly computed at the plot level using yield and cost ATT estimates. Specifically, for household i's plot k planted with an improved maize variety, the income change $\Delta\hat{I}_{ik}$ is computed as:

$$\Delta\hat{I}_{ik} = \left(PY_{ik}^{OBS} - C_{ik}^{OBS}\right) - \left(PY_{ik}^{CT} - C_{ik}^{CT}\right) = P\Delta\hat{Y}_{ik} - \Delta\hat{C}_{ik} \quad (8)$$

where P is the unchanging maize price; (Y^{OBS}, C^{OBS}) and (Y^{CT}, C^{CT}) are observed and counterfactual yield and cost pairs of plot k, and $\Delta\hat{Y}_{ik}$ and $\Delta\hat{C}_{ik}$ denote the differences in yield and cost due to adoption, respectively, calculated using estimated treatment effects. Household-level income changes are then computed as the summation across all maize plots of the household with improved maize varieties:

$$\Delta\hat{I}_i = \sum\nolimits_k \left(P\Delta\hat{Y}_{ik} - \Delta\hat{C}_{ik}\right). \quad (9)$$

The counterfactual income for each adopting household is obtained by subtracting $\Delta\hat{I}_i$ from the observed income of household i. The counterfactual income distribution is obtained by aggregating all these individual effects.

In a closed economy, it is difficult to directly estimate household income changes because household demand and supply respond to the price changes, and such responses are not measurable at the household level. Thus, it is necessary to estimate market-level changes in prices and economic surplus, and then allocate surplus changes to appropriate households. An economic surplus model is employed in estimating market-level impacts.[1] The key parameter affecting price and economic surplus change is the cost reduction per unit of output due to adoption, or the k-shift (Alston et al., 1995):

$$K = \left(\frac{\hat{\phi}}{\varepsilon} - \frac{\hat{\theta}}{1+\hat{\phi}}\right) \times \text{Adoptionrate}, \quad (10)$$

[1] In the partial equilibrium framework, it is assumed that other markets (e.g., labor, input) undergo no systematic change. A major concern is that aggregate impacts may be affected if labor markets are incomplete. To carefully account for any possible market incompleteness, we estimate and employ shadow prices for both labor and ox power in the cost function estimation, as detailed below.

where ε is the supply elasticity; $\hat{\phi}$ and $\hat{\theta}$ are yield and cost ATTs estimated through Eqs. (5) and (7). The yield and cost ATTs from MTE estimation are employed in Eq. (10) to compute the k-shift, and plot-specific yield and cost treatment effect estimates are used in allocation to account for possible treatment effect heterogeneity.

Using the estimated k-shift, the counterfactual output price level that would have existed if there were no adoption of improved maize varieties, is retrieved. It can be shown that the counterfactual equilibrium price can be obtained using Eq. (11):

$$P^{CT} = P^{OBS}(\varepsilon + \eta)/(\varepsilon + \eta - K\varepsilon), \quad (11)$$

where η is the absolute value of the demand elasticity. Q^{CT} is computed by subtracting the aggregate yield gains from Q^{OBS}. The following formulas estimate changes in aggregate producer and consumer surplus (Alston et al., 1995), where Z equals the proportional reduction of market price, $(P^{CT} - P^{OBS})/P^{CT}$:

$$\Delta PS = P^{CT} Q^{CT} (K - Z)(1 + 0.5Z\eta) \quad (12)$$

$$\Delta CS = P^{CT} Q^{CT} Z (1 + 0.5Z\eta). \quad (13)$$

In this framework, the counterfactual is conceived of as the market equilibrium that would exist in the absence of the new technology. Measures of changes in surplus correspond to a single national market at a single point in time.

3.3. Allocation of surplus changes

Next, market-level producer and consumer surplus changes are allocated to households. On the demand side, only maize buyers experience consumer surplus gains due to a lower price. Thus, ΔCS is allocated to households (using appropriate sample weights) according to their purchased quantities as a share of total market supply.

The allocation of producer surplus change is more complicated as welfare impacts vary by household net sales position and adoption status. Specifically, all maize sellers suffer from a lower market price while adopters may still be better off if their per-unit cost reduction is large enough to offset the price drop or if their maize sales are small. To differentiate these confounding effects, we first decompose the aggregate producer surplus change into a price effect and an adoption effect:

$$\Delta PS = \Delta PS_{PRICE} + \Delta PS_{ADOPTION}. \quad (14)$$

Direct computation of $\Delta PS_{ADOPTION}$ is difficult as households experience different yield and cost changes. However, it is possible to compute ΔPS_{PRICE} at the market level as price change is unique for all market participants. Mathematically, it can be shown that:

$$\Delta PS_{PRICE} = \frac{K\varepsilon P^{OBS} Q^{CT}}{\varepsilon + \eta - K\varepsilon}\left(\frac{K\varepsilon P^{OBS}}{2P^{CT}(\varepsilon + \eta - K\varepsilon)} - 1\right) \quad (15)$$

Table 1
Descriptive statistics of maize households by adoption type[a]

	Adopters ($n = 503$)	Nonadopters ($n = 583$)[b]	Partial-adopters ($n = 273$)[b,c]
Total cultivated area (ha)	2.02 (1.51)	1.86 (1.33)	2.37**,††† (1.89)
Total maize area (ha)	0.709 (0.674)	0.553*** (0.545)	1.09***,††† (1.17)
Household size	6.58 (2.46)	6.29** (2.21)	6.91*,††† (2.40)
Total household wealth[d] (thousand ETB)	18.8 (35.3)	13.2 (29.5)	22.7***,††† (61.2)
Head gender (% of male)	95.0 (21.8)	91.3** (28.3)	98.1**,††† (13.4)
Head age (years)	42.0 (13.0)	43.9** (12.5)	43.2 (11.3)
Head marital status (% married and living together)	94.6 (22.6)	90.6** (29.3)	96.7††† (17.9)
Head education (years)	2.92 (3.36)	2.48** (2.99)	2.99††† (3.32)
Head illiteracy rate[e]	0.549 (0.492)	0.592 (0.498)	0.582 (0.494)

[a]Standard deviations are in parentheses.
[b]*, **, *** indicate significance at 1%, 5% and 10% level in pairwise t-tests with adopters.
[c]†, ††, and ††† indicate significance at 1%, 5% and 10% level in pairwise t-tests with nonadopters.
[d]Computed as the sum of the self-reported values of all household assets and measured in Ethiopian Birrs (ETB). The daily average exchange rate in 2010 is 1 USD = 14.38 ETB.
[e]Defined as no education at all, as opposed to at least some education.

$\Delta PS_{ADOPTION}$ is then computed as the residual between ΔPS, evaluated through equation (12), and ΔPS_{PRICE} as computed above.

ΔPS_{PRICE} is allocated to all maize sellers, who suffer from the price drop, based on their market shares. Productivity and cost changes affect all adopting plots, to which $\Delta PS_{ADOPTION}$ is allocated. Specifically, the allocation is done using the weight w_i for adoption plot i with the area of A_i and per unit cost reduction K_i computed using plot-specific cost and yield MTEs through Eq. (10):

$$w_i = \frac{K_i A_i}{\sum_i K_i A_i}. \tag{16}$$

The plot-specific adoption benefits are then aggregated to the household. This procedure fully accounts for partial adoption, direct benefits from adoption, and indirect effects from market price change. The counterfactual income of each household is computed by subtracting the income change from the observed household income.

3.4. Poverty impact estimation

Two counterfactual income distributions corresponding to the open and closed economy cases are derived. Foster–Greer–Thorbecke (FGT) poverty indices (Foster et al., 1984) are then computed with alternative poverty lines using the observed and counterfactual incomes. The poverty impacts, in terms of reduction in the poverty headcount ratio, depth, and severity are measured as the difference in the respective poverty indices. Sensitivity analyses are implemented to check the robustness of these poverty impact estimates.

4. Data description

The data come from a household survey conducted jointly by CIMMYT and EIAR in 2010. Four regions are covered: Oromia, Amhara, Tigray, and Southern Nations, Nationalities, and People's Region (SNNPR), which together account for more than 93% of maize production in Ethiopia (Schneider and Anderson, 2010). A stratified random sampling strategy is used where strata are randomly selected woredas (districts) of high, medium and low maize yield potential. The data are nationally representative with regional differences in maize productivity accounted for. A total of 1,396 farm households from 30 woredas were surveyed; of these, 1,359 grow maize on 2,496 plots (46.4% households own only a single maize plot). Plot areas are reported by farmers and details of crop production such as varieties, yields, and inputs are recalled.

Maize varieties can be grouped into three categories: hybrids, improved open-pollinated varieties (OPVs), and local open-pollinated varieties. Hybrid maize has the highest yield, but requires the purchase of new seeds for each cropping season to restore hybrid vigor and the seeds cost more than OPVs. OPVs generally have lower yields than hybrids (still higher than local varieties) but the seeds may be recycled for up to three seasons. Many OPVs are developed for challenging conditions (e.g., droughts, pests) and areas where seed markets are underdeveloped. Whatever varieties farmers grow, inbred lines are crossed through open pollination. Thus, for this study, varieties are only differentiated as being either improved or local.[2] As suggested by local maize breeders, any hybrid that has been ever recycled or OPV that has been recycled for more than three seasons is categorized as local. No further differentiations are made among improved maize varieties because variety-specific estimation is not possible due to sample size considerations. There is no dominant variety and hybrids are

[2] There are several reasons for this categorization. First, the pollination process is not controlled and varieties may cross with each other if plots are close. Second, OPVs are a collection of varieties with features such as drought tolerance and pest resistance, which might not come into play in the specific year of 2010. Third, the mean per-hectare yields of hybrids and OPVs in the data differ only with marginal significance. See Fig. 1 for the kernel density estimations of yields by variety types.

Table 2
Summary of plot characteristics and maize cropping practice

	Improved[a] ($n = 1214$)	Local[a] ($n = 1282$)	Difference[b]
Plot characteristics			
Altitude (m)	1832.5 (304.5)	1830.1 (255.4)	2.4 (.832)
Walking minutes from home	9.73 (18.43)	14.26 (28.87)	−4.53 (0.000)
Plot area (ha)	0.453 (0.416)	0.334 (0.357)	0.119 (0.000)
Soil slope (1–3: gentle-medium-steep)	1.43 (0.65)	1.52 (0.70)	−0.11 (0.002)
Soil depth (1–3: shallow-medium-deep)	2.21 (0.84)	2.17 (0.85)	0.05 (0.162)
Soil fertility (1–3: good-average-poor)	2.45 (0.62)	2.47 (0.60)	−0.02 (0.359)
Maize cropping practice			
Season (1 = long; 0 = short)	0.945 (0.228)	0.915 (0.279)	0.030 (0.003)
Intercropping (1 = yes; 0 = no)	0.129 (0.266)	0.173 (0.384)	−0.044 (0.135)
Labor days per ha	105.0 (115.4)	102.9 (78.5)	2.1 (0.588)
Ox plow days per ha	8.01 (7.87)	4.92 (4.63)	3.09 (0.000)
Fertilizer (kg per ha)	150.6 (243.3)	56.3 (305.8)	94.3 (0.000)
Other inputs per ha[c] (ETB[d])	299.1 (398.9)	67.7 (210.8)	231.4 (0.000)
Yield (kg per ha)	3434.9 (2176.2)	2159.6 (1610.8)	1275.2 (0.000)
Input cost (ETB per ha)	2133.2 (39.7)	1638.4 (32.5)	494.8 (0.000)

[a]Standard deviations are in parentheses.
[b]*P*-values of *t*-tests of differences by maize varieties are in parentheses.
[c]Including cost of purchased seeds and pesticides.
[d]The daily average exchange rate in 2010 is 1 USD = 14.38 ETB.

generally more popular than OPVs. After accounting for sampling weights, our data suggest an adoption rate of improved maize of 39.1% by area.

Among the 1,359 households, there are 503 adopters, 583 nonadopters, and 273 partial adopters (Table 1). Larger and wealthier land holders with more family members tend to adopt improved varieties, while partial adopters have the largest total cultivated area, maize area and household size. Adopting household heads are more likely to be male, younger, married and better educated. The survey also asks about the intention to adopt improved maize varieties. Results show that adoption is likely increasing over time as 71.7% of nonadopters are interested in adoption in the future.

Table 2 summarizes plot characteristics and farmers' maize cropping practices. Maize is mainly cultivated in the long rainy season (June to September, 2,320 plots in total) as compared to the short rainy season (February to April, 176 plots in total). Inputs such as oxen power, fertilizer, and other inputs, including purchased seeds and pesticides, are reported in monetary terms, which appear to be significantly higher for adopting plots. Labor use does not vary by variety. Improved varieties yield about 1,275 kg more dry maize per hectare than local varieties, a 59.0% yield difference (Figure 1). Using shadow prices of labor and ox plow computed following Jacoby (1993, see more details below), the total input cost associated with improved maize varieties are 30.2% higher than local varieties.

Table 3 describes household characteristics by poverty status, which is evaluated using household income per person per day. Total household income is computed as the sum of the total market value of self-reported crop and livestock production, transfers, and other sources of income. Concerns about income underreporting (e.g., McKay, 2000) are minimized by aggregation over itemized sources instead of a single value. Three

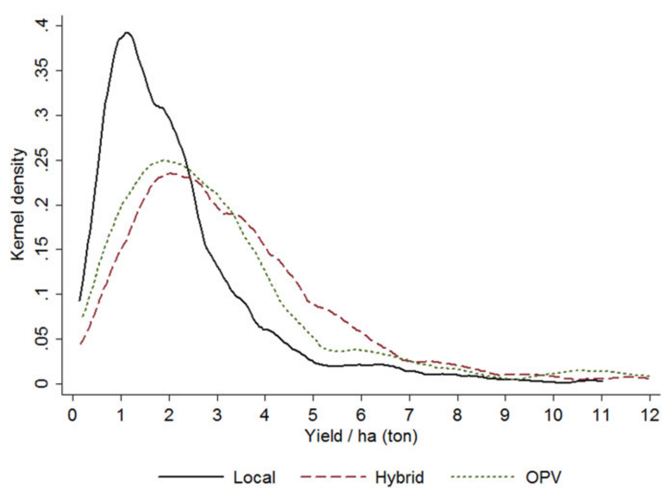

Fig. 1. Kernel density estimation of yields of different maize varieties.

poverty lines are employed: \$1, \$1.25, and \$1.45 per person per day,[3] which roughly represent a 95% confidence interval for the mean poverty line for the poorest 15 countries including Ethiopia (Chen and Ravallion, 2010). Poor households are larger in size, and own assets that total about one-half of the monetary value of those of the nonpoor. The observed poverty headcount ratios are noticeably higher among nonadopters.

[3] Average exchange rates in 2010 are employed to convert Ethiopian birrs to U.S. dollars.

Table 3
Descriptive statistics of household characteristics by poverty status[b]

Poverty line ($ per person per day)	$1		$1.25		$1.45	
Poverty status	Nonpoor (n = 955)	Poor (n = 404)	Nonpoor (n = 778)	Poor (n = 581)	Nonpoor (n = 667)	Poor (n = 692)
Household size	6.191	7.317***	6.057	7.153***	5.954	7.077***
Total assets (ETB)[b]	20,220	10,010***	22,076	10,635***	23,680	10,924***
Head gender (1 = M; 0 = F)	0.934	0.955	0.936	0.947	0.934	0.947
Head age (years)	42.80	43.63	42.70	43.52	42.83	43.27
Head marital status (1 = married; 0 = other)	0.924	0.955**	0.923	0.947*	0.922	0.945
Head education (years)	2.902	2.376***	2.960	2.458***	2.988	2.512***
Head illiterate (1 = yes; 0 = no)	0.520	0.594**	0.528	0.604***	0.537	0.607***
Poverty headcounts among nonadopters	32.76%		46.14%		55.40%	
Poverty headcounts among full adopters	28.03%		40.36%		47.11%	
Poverty headcounts among partial-adopters	26.37%		39.93%		48.35%	

[a]***, **, * denote that the difference between nonpoor and poor is significant at 1%, 5%, and 10% level via *t*-test, respectively. Computed as the sum of the self-reported values of all household assets.
[b]Household income per person per day is used as the welfare measure. Official daily average exchange rate in 2010 is used.

5. Results

5.1. Estimating treatment effects

The treatment effects of adoption on productivity and costs are estimated using a production and cost function, respectively. On the production function side, explanatory variables are per-hectare inputs (labor days, ox plowing days, amount of fertilizer and other capital inputs, all in logarithmic form), human capital indicators (total household size and wealth, characteristics of household head such as gender, age, marital status, education), maize area, soil characteristics (slope, depth and fertility, on discrete scales), seasonal dummy (short or long), village altitude, and regional dummies.

Due to endogeneity of the adoption decision, IV techniques are employed (Suri, 2011). The instruments should affect adoption, but only affect the outcome (yield or cost) through their impacts on adoption. Five potential IVs are used in yield ATT estimation: the distances to the nearest seed dealer, agricultural extension office, farmer cooperative and main market, and the quality of roads to the main market.[4] These IVs reflect the accessibility of improved seeds, extension services, credits and the degree of commercialization. They also capture resource accesses at different geographical scales ranging from village-level (agricultural extension office) to woreda-level (main market).

The IVs are chosen after in-depth discussions with international and local experts. Access to markets and other services might affect input use in production (such as fertilizer and labor) due to transportation and other costs, and it may be argued that access might have an additional (direct) effect on yield. However, in a well-specified production function where levels of inputs are already controlled for, access to such resources should not affect maize yield other than through its impact on adoption. If improved seeds were randomly distributed to farmers in a randomized controlled trial, a proper production function would include input levels, the variety used, and other variables reflecting the technical relationship between inputs and outputs. A variable such as distance to seed dealer would have no place in such a model. Thus, their exclusion in a production function approach when variety choice is treated as endogenous is perfectly acceptable. Similar logic holds for the other variables. For example, it might be argued that roads are placed in areas with higher fertility and, hence, might not legitimately be excluded from the outcome equation. However, our production function already includes variables accounting for soil fertility, and the exclusion of road quality in the outcome equation is logical because the variable mediating the relationship is already controlled for. Similar IVs have been used in literature. For example, Suri (2011) uses the distance to the nearest fertilizer dealer as an IV in estimating maize production functions in Kenya. In addition to the intuitive justification, these IVs also pass a series of tests concerning IV suitability (details are provided in the Data Appendix).

A Cobb-Douglas production function is estimated via 2SLS, Probit-2SLS and GMM procedures to reveal yield ATT, or $\hat{\phi}$. Alternative estimates under heterogeneity are obtained by the overall ATT evaluated using plot-specific MTEs, as described previously. As reported in the upper panel of Table 4 (and full estimation results in the Data Appendix), the results from the different estimation procedures are numerically close. Depending on the model, $\hat{\phi}$ is estimated to be between 47.6% and 63.3%. A flexible translog functional form is also estimated, and $\hat{\phi}$ is estimated as 53.5–61.6%. This closeness builds confidence in the estimates.

Estimated yield MTEs are highest among mid-low propensity scores (Fig. 2). These results indicate negative selection: farmers are less likely to grow improved varieties on plots

[4] Another potential IV is the self-reported adoption history of improved maize varieties. However, this variable is missing for about one-third of the observations. Use of this IV with the two-thirds sample led to very similar ATT estimates to the main result. Since this IV does not add much to the model, the results with the full set are reported.

Table 4
Estimation of yield and cost ATTs[a]

ATT	Model specification	Homogeneity 2SLS	Homogeneity Probit-2SLS	Homogeneity GMM	Heterogeneity LIV
Yield effect	Cobb–Douglas	0.588 (0.170)	0.476 (0.128)	0.561 (0.145)	0.633 (0.242)
	Translog	0.616 (0.170)	0.564 (0.126)	0.594 (0.146)	0.535 (0.203)
Cost effect	Cobb–Douglas	0.276 (0.113)	0.228 (0.084)	0.261 (0.102)	0.278 (0.110)
	Translog	0.243 (0.097)	0.231 (0.089)	0.239 (0.110)	0.253 (0.098)

[a]Standard errors of the treatment effects are reported in parentheses. 2SLS standard errors are clustered at the woreda level (the primary sampling unit). LIV standard errors are obtained by bootstrapping (100 times). Full estimation results are provided in the Data Appendix.

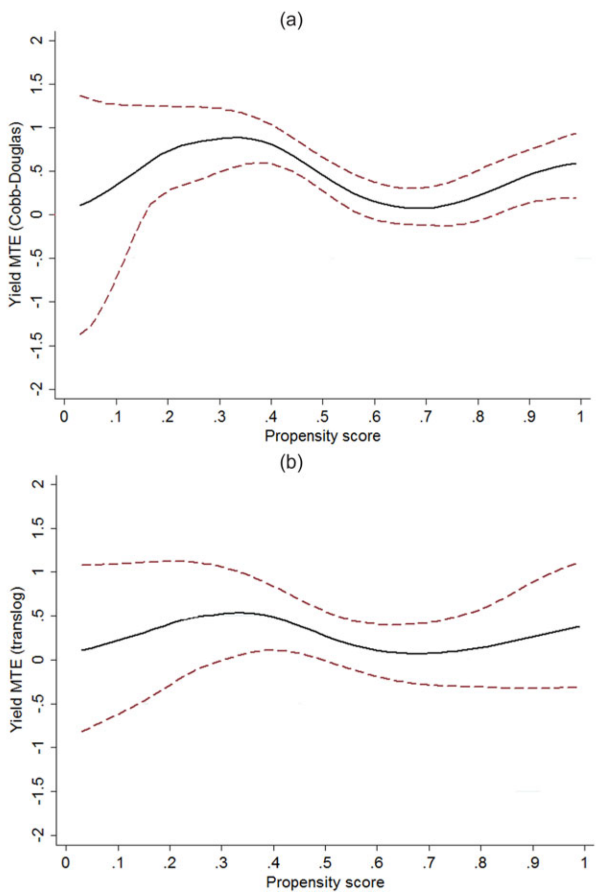

Fig. 2. Yield marginal treatment effect estimation.†
†Estimated using local polynomial regression. Solid line shows the estimated MTE; dashed lines are 95% confidence intervals obtained via bootstrapping.

that are more likely to observe a higher yield gain, a pattern also found in Suri (2011). As about half the households grow maize on a single plot, negative selection indicates that farmers planting maize on plots with higher yield potential may be more conservative. As a test for treatment effect heterogeneity, OLS regressions were run of the estimated MTEs on propensity scores, with the null hypothesis being a zero slope. Similar to Suri (2011), the slopes are found negative and significant at 1% level, confirming the existence of heterogeneity.

The cost ATT, or $\hat{\theta}$, is estimated in a similar manner. Explanatory variables include the prices of inputs (labor, fertilizer, ox plow, and pesticide)[5] , maize yield per hectare, maize area, plot and household characteristics, and season and regional dummies. Only three of the five IVs are included in the cost effect estimation: distances to the nearest extension office, farm corporative and seed dealer. Distance and quality of road to the main market are excluded as they may affect total cost in unobserved ways. The three IVs are intuitively justified in a similar manner as input prices are already controlled for in the cost function specification. They also pass a battery of tests concerning IV suitability. Results are reported in the lower panel of Table 4. $\hat{\theta}$ is estimated to be a 22.8–27.8% cost increase under a Cobb-Douglas specification and a 23.1–25.3% cost increase under a translog specification.

Estimated cost MTEs also generally decrease as propensity scores increase (Fig. 3). Regressions of MTE on propensity scores yield a negative slope with 1% significance, confirming the existence of heterogeneity in cost ATT as well. These results offer a possible explanation for the negative selection observed in yield MTEs: high costs of additional inputs discourage adoption even if the yield potential is high.

5.2. Robustness checks

PSM is implemented as a means of robustness check for the estimates of both yield and cost ATTs. A plot-level probit model is first estimated to obtain propensity scores, where the explanatory variables include plot-level characteristics (soil slope, depth and fertility, cropping season, plot area and altitude), household characteristics (the size and asset value of household; gender, age, age square, literacy and marital status of household head), regional dummies as well as the five IVs that measure access to resources. Balancing tests are performed and no systematic differences in the distribution of covariates between treated and untreated groups are suggested (see the Data Appendix).

Three matching techniques are employed: nearest neighbor matching, radius matching, and kernel matching. The yield ATT

[5] Following Jacoby (1993), shadow prices of labor and ox plow are computed from production function estimates of the respective marginal product of labor and animal power, and employed here.

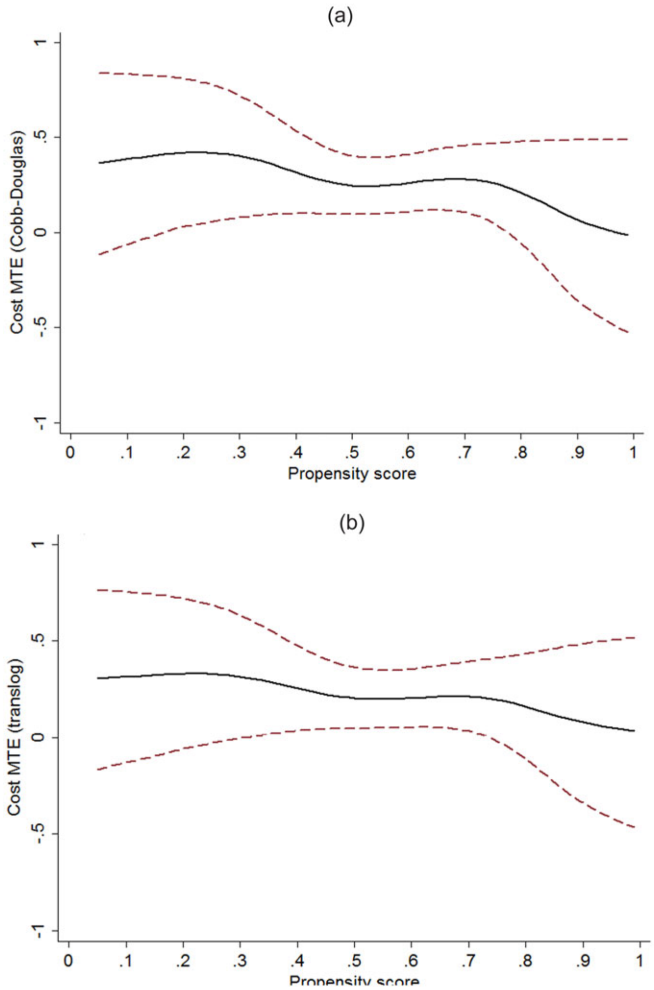

Fig. 3. **Cost** marginal treatment effect estimation.†
†Estimated using local polynomial regression. Solid line shows the estimated MTE; dashed lines are 95% confidence intervals obtained via bootstrapping.

is estimated to be 43.4–48.9% (all with 1% significance). PSM also estimates cost ATT, which appears to be 22.1–25.6% (with at least 5% significance). These ATTs are numerically close to our econometric estimates.

Finally, the yield ATT $\hat{\theta}$ is estimated using the subsample of 273 partial adopters with 772 plot-level observations. $\hat{\phi}$ is estimated as the difference in productivity between improved and traditional plots of the same farm household. The model is specified as the differences in adopting and nonadopting plots in Eq. (4):

$$\Delta y_{ikl} = \phi + \beta_{kl} \Delta X_{ikl} + \Delta u_{ikl}, \tag{17}$$

where the difference is taken between the plot k (improved) and plot l (local) for the ith household; β_{kl} is equal to $(\beta^1 - \beta^0)$ and ΔX_{ikl} is the vector of input differences. This vector of input differences cancels out observed and unobserved household-level heterogeneity, and the yield ATT is identified as the constant ϕ. OLS regressions using Cobb-Douglas and translog specifications suggest 38.7% and 42.1% yield increases, respectively, both significant at 5%. These results again lend credence to our previous estimates.

Although the first-difference type procedure in Eq. (15) does not apply to cost function estimation, as the same household cannot differentiate input prices among plots, we are able to compute the difference in average per-hectare total input costs between adopting and nonadopting plots among partial adopters. Shadow prices for labor and ox plow used, growing improved maize varieties indicate an average of 33.4% cost increase with adoption. All these robustness checks support our main results.

5.3. *Estimating counterfactual income distribution*

Given the confirmed heterogeneity in both yield and cost MTEs, the LIV estimates are employed to estimate the counterfactual income distribution. In the small open economy, poverty impacts are easily estimated using yield and cost MTEs since the maize market price does not change as productivity-related supply shifts occur. For the closed economy, a natural next step is to obtain price elasticities of supply and demand to derive the counterfactual price level. Given the cross-sectional nature of our data and the lack of demand side information, the elasticities are synthesized from existing literature, followed by sensitivity analyses for robustness check of poverty estimates. From the large literature on maize supply and demand elasticities in Sub-Saharan Africa (e.g., Abrar et al., 2004; Alene et al., 2008; Jayne et al., 1995), we assume a supply elasticity of 0.5 and a unit absolute value of demand elasticity.

The market price P^{OBS} is obtained as an average of national-level annual producer prices over 2000–2010 from FAOSTAT, which is 0.166 U.S. dollar per kilogram.[6] With P^{OBS}, the k-shift is computed as a 37.4% cost reduction per kilogram of maize. A P^{CT} of 0.191 U.S. dollars per kilogram is obtained by averaging the LIV estimates from the Cobb-Douglas and translog technologies. At the national level (3.897 million metric tons of maize production in 2010, FAOSTAT), the total changes in producer surplus and consumer surplus are USD 130.40 million and 65.20 million, respectively.[7] According to the maize production share of surveyed households over the national-level production, a USD 75118 producer surplus gain (with ΔPS_{PRICE} of USD -32929 and $\Delta PS_{ADOPTION}$ of USD 108047) and a USD 37559 consumer surplus gain are allocable to surveyed households.[8] The data also suggests that only 6.37% of the consumer

[6] The producer price is used as retail price statistics are limited. The 11-year average is used since a price peak is observed during 2007–2009 due to the global commodity price spike, and our final poverty impacts are conservative.

[7] For comparison, the economic surplus change (only ΔPS) in the small open economy is USD 175.13 million.

[8] It is assumed that farm households in un-surveyed areas are similar to those in the surveyed areas. This makes sense as our data is representative of all maize producers in Ethiopia. Sample weights are used to make inferences to the broader maize-producing population.

Table 5
Poverty impacts of improved maize varieties

Poverty line (USD per person per day)	FGT poverty index	Observed	Small open economy	Poverty impact†	Closed economy	Poverty impact†
1	Headcount	0.2894	0.2987	0.0093	0.2973	0.0079
	Depth	0.0963	0.0994	0.0031	0.0991	0.0028
	Severity	0.0435	0.0453	0.0018	0.0449	0.0014
10.25	Headcount	0.4162	0.4291	0.0129	0.4255	0.0093
	Depth	0.1496	0.1534	0.0038	0.1537	0.0041
	Severity	0.0724	0.0748	0.0024	0.0749	0.0025
10.45	Headcount	0.4957	0.5057	0.0100	0.5043	0.0086
	Depth	0.1947	0.1996	0.0049	0.1992	0.0045
	Severity	0.0983	0.1021	0.0038	0.1020	0.0037

†All poverty impacts are reported as percentage point reductions compared to the counterfactual.

surplus change goes to maize producing households[9], and thus almost all measured welfare impacts occur through producer surplus changes. Benefits for maize-producing households average 2.4 U.S. cents per person per day, but some households benefit by much more and some by much less, depending on the yield and cost MTEs.

5.4. Assessing poverty impacts

The counterfactual and observed income distributions are used to measure poverty. As discussed above, three poverty lines (\$1, \$1.25 and \$1.45 per person per day) are employed. The poverty impacts are assessed using previously estimated MTEs.

Poverty decreases as a result of adoption of improved maize (Table 5). Impacts on the poverty headcount reduction is slightly larger in the small open economy (0.9–1.3 percentage points) as compared to the closed economy (0.8–0.9 percentage points). This is intuitive as maize profitability decreases as market price drops, and only a small portion of total consumer surplus is enjoyed by maize producers. These numbers further imply that 1.7–3.1% of the rural poor maize producers have escaped poverty in the current year due to adoption of improved maize.[10] The depth and severity estimates show similar patterns, and generally suggest a 2.3–3.1% decrease in poverty depth and a 3.1–4.0% decrease in poverty severity. Such results are robust across all poverty lines. We further implement sensitivity analysis where joint variations of key parameters, including estimated treatment effects ($\hat{\phi}$ and $\hat{\theta}$), elasticities (ε and η), the adoption rate and the producers' proportion of maize purchase are allowed for. Results suggest the current poverty estimates are slightly above the lower bounds and are thus rather conservative.[11]

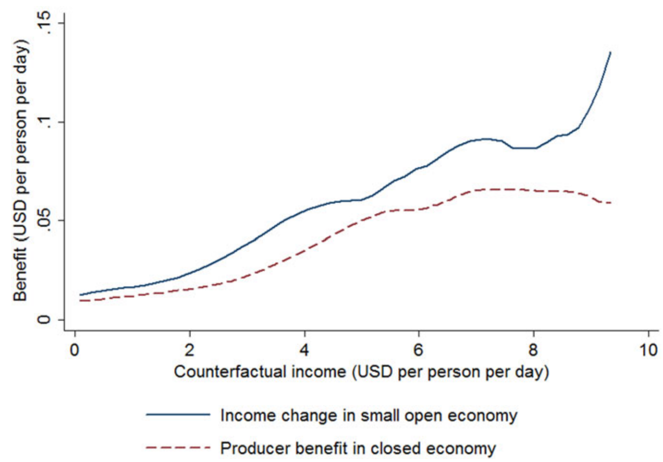

Fig. 4. Benefits due to adoption across counterfactual income levels.†
†Counterfactual incomes of 95% households are less than 5 USD per person per day. About 1% households with counterfactual incomes above 10 USD per person per day are excluded.

A 0.8–1.3 percentage point reduction in the poverty headcount ratio implies that 63.7–103.6 thousand households in rural Ethiopia have escaped poverty due to adoption. Less pronounced improvements also exist in poverty depth and severity. These changes reflect the poverty impact on maize producers of maize CGI research in Ethiopia.

Although the overall poverty impacts are substantial, benefits may not have been equal. To explore the distribution of impacts, the relationship between allocated producer surplus of adopting households and their counterfactual income levels are explored through local polynomial regressions (consumer benefits are ignored due to small magnitudes). As seen in Fig. 4, poor adopters are found to benefit the least. While poor farmers are further found as likely to adopt as the nonpoor, and their yield and cost MTEs are similar, they are able to adopt on far smaller areas. The smallness of land holdings, rather than inability to adopt, explains why the poor receive few benefits.

[9] The poverty impacts among pure consumers (e.g., urban households) cannot be accounted for because they are not included in the survey. Thus, final poverty impacts reflect changes in poverty among maize producers.

[10] Computed as the percentage reduction divided by the counterfactual poverty headcount ratio. For example, in the small open economy, the counterfactual poverty headcount ratio and poverty impact under the \$1 poverty line are 0.2987 and 0.0093, respectively. Thus, the percentage of the originally poor who have escaped poverty is 0.0093/0.2987 = 0.0311, or 3.1%. Similar computations are applied to poverty depth and severity.

[11] Details are available upon request.

6. Concluding remarks

Maize research and subsequent adoption of research-produced technologies have had substantial impacts on poverty in rural Ethiopia. A one or two percent reduction in overall poverty headcounts due to improved maize varieties alone is a major achievement. This study employs cross-sectional household survey data and estimates poverty impacts for a single year with the counterfactual of zero adoption. The poverty impacts should grow over time with increasing adoption rate (as most nonadopters are willing to adopt improved maize varieties in the future), expansion of maize area and increased maize consumption. Also, as most consumer surplus gains go to urban consumers, who are not included in this study, country-wide reductions in poverty should be greater than those estimated here. Our findings indicate that research investments in maize CGI should be continued and extension efforts be enhanced to promote further adoption if poverty reduction remains a target. Improved maize seeds with refined and more diverse traits can be developed to meet specific needs under a greater range of agroecological and socioeconomic conditions. Also, agricultural extension and seed sector efficacy should be strengthened to promote adoption among farmers.

Benefits of maize CGI research are, however, unevenly distributed; the poor received few benefits from adoption due to limited land holdings. Although no evidence is found that poor farmers are inhibited from adopting improved maize varieties, adoption promotion services, especially those targeting poor nonadopters cannot be overemphasized. Other microlevel policies that aim to secure and increase benefit flows to poor farmers might be further explored, which might include enhanced access to key resources such as market information, varietal knowledge, inputs and credit.

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