Ex-Post Impacts of Improved Maize Varieties on Poverty in Rural Ethiopia

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Abstract: A procedure is developed to examine the ex-post impacts of improved maize varieties on poverty in rural Ethiopia. Yield and cost effects of adoption are estimated econometrically under assumptions of both homogeneous and heterogeneous treatment effects. A backward derivation procedure is employed within an economic surplus framework using estimated treatment effects to identify the counterfactual income distribution without improved maize varieties. Poverty impacts are estimated as the differences in poverty indices computed using observed and counterfactual income distributions. Improved maize varieties have led to noticeable reduction in the poverty headcount ratio, depth, and severity in rural Ethiopia. However, poor producers benefit the least from adoption because their land areas are limited.

Key Words: improved maize varieties, poverty, impact, rural, Ethiopia

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 contribute to poverty reduction and food security. Despite substantial investments in agricultural research over time, there are relatively few empirical studies of the poverty or other distributional impacts of improved crop varieties in Sub-Saharan Africa. Policy makers need information on these impacts to allocate resources to fruitful lines of research and to take steps to strengthen the role of agricultural research in poverty reduction.

Maize is a widely grown food and cash crop in many environments in Sub-Saharan Africa. In Ethiopia, maize accounts for the largest share of production by volume and is produced by more farms 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), were developed and released in Ethiopia by the Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the International Maize and Wheat Improvement Center (CIMMYT). This article investigates the impact of these improved maize varieties on poverty.

Several empirical issues are addressed. Partial adoption is observed: the adoption of improved maize varieties on only a portion of a household's maize area. As a result, adoption decisions are non-binary at the household level. Therefore, the analysis is conducted at the plot-level, and the subsample of partial adopters is used to check for robustness. Heterogeneity is considered in treatment effects (yield and cost increases due to adoption) across plots and farm households, and poverty impacts are investigated under heterogeneity. Instrumental variable (IV) techniques, including a local IV (LIV) approach, are used as the main identification strategy. A backward derivation procedure is developed using an economic surplus framework to identify the counterfactual income distribution. Poverty impacts are measured as the differences between poverty indices computed with the observed and the counterfactual income distributions.

Background

Crop genetic improvement has led to substantial increases in food production worldwide (Evenson and Gollin, 2003), and it contributes to poverty reduction through multiple channels. At the farm-household level, benefits are obtained via adoption, which in turn is affected by education (Lin, 1991), wealth (Langyintuo and Mungoma, 2008), risk attitude (Koundouri, Nauges and Tzouvelekas, 2006; Dercon and Christiaensen, 2011), profitability as compared to alternatives (Suri, 2011); seed supply and access constraints (Shiferaw, Kebede and You, 2008); and information about the new technology (Conley and Udry, 2010; Maertens and Barrett, 2012) among other factors.

Field-level impacts of improved maize varieties can be considered as "treatment effects", where the treatment is technology adoption. Adoption increases productivity, but cost increases (seed and other input costs) can partially offset positive direct income effects of a yield gain. As productivity gains are aggregated over many adopters, market-level indirect effects emerge; market prices fall creating benefits to consumers and adversely affecting farm incomes.

Most econometric analyses of treatment effects are based on the potential outcomes framework (Rubin, 1974), where each observed unit has a potential outcome in the treated and untreated state. We observe the outcome of interest of each unit (plot) as either treated (adopting) or untreated (not adopting), but not both. Specifically, let T be a binary indicator of treatment status (0 = not treated; 1 = treated), and y^T be the outcome of interest (crop yield or input costs). For each unit (plot) the difference in average outcomes, or the naive average treatment effect estimate, is (covariates suppressed):

$$\text{(1)} \qquad \mathrm{E}[y^1 \mid T=1] - \mathrm{E}[y^0 \mid T=0] = \mathrm{E}[y^1 - y^0 \mid T=1] + \{\mathrm{E}[y^0 \mid T=1] - \mathrm{E}[y^0 \mid T=0]\}$$

The right hand side of equation (1) consists of two terms: the average treatment effect on the treated (ATT) and selection bias. The latter occurs in non-experimental studies where the assignment of treatment (individual decision makers decide to adopt) is non-random. Specific strategies are needed to eliminate selection bias and identify the treatment effect under this endogeneity. Matching (Mendola, 2007; Becerril and Abdulai, 2010; Dillon, 2011; Kassie, Shiferaw and Muricho, 2011) and instrumental variable (IV) techniques (Matuschke, Mishra and Qaim, 2007; Minten and Barrett, 2008; Dercon et al., 2009) are the most widely used. Matching imposes the strong assumption that all determinants of selection are observed in the treatment. Use of IVs assumes that the IVs are uncorrelated with the error term in the outcome equation. It can also be difficult to find suitable IVs.

Possible differences in treatment effects across plots and households must be considered. Treatment effect heterogeneity can be associated with observed and unobserved characteristics of plots (e.g. fertility) and households (e.g. managerial skill). Recent literature on treatment effect heterogeneity has yielded a number of promising approaches. For example, the local average treatment effect (LATE) (Imbens and Angrist, 1994) identifies the treatment effect among compliers with the treatment. Quantile IV regression (Chernozhukov and Hansen, 2005) investigates heterogeneous impacts on different percentiles of the treatment effect distribution. The marginal treatment effect (MTE) procedure estimates heterogeneous treatment effects across estimated propensity scores: the probabilities of being treated (Björklund and Moffitt. 1987; Heckman, Urzua and Vytlacil, 2006). A control function approach has also been developed for cases in which the treatment is continuous and endogenous (Florens et al., 2008). While the literature continues to grow, a gap remains between econometric theory and empirical applications. We use the MTE procedure proposed in Heckman, Urzua and Vytlacil (2006) because of the binary plot-level treatment and the difficulties in assessing population-level poverty impacts using LATE estimates.

Once plot-level treatment effects are obtained, a market model is used to account for indirect income effects. Indirect effects occur when the diffusion of improved crop varieties causes market price changes, and both producers (adopters and non-adopters) and consumers are affected (de Janvry and Sadoulet, 2002). Regardless of methods, a key to effective impact assessment is specification and identification of the counterfactual—what would have happened in the absence of the treatment. The counterfactual can be found in an economic surplus framework using a backward derivation procedure. A natural link exists between plot-level treatment effects and market-level impacts, and the former can be aggregated to identify the market-level counterfactual.

Modeling Procedure

The modeling procedure consists of three steps. First, treatment effects are identified in terms of yield and cost changes due to adoption. Second, direct and indirect effects on income are the identified using estimated treatment effects. Third, poverty impacts are estimated via comparisons of poverty indices computed using observed and counterfactual income distributions.

Treatment effect specification

The household is the basic unit in most micro-econometric assessments of CGI impacts, and most empirical studies classify households as either adopters or non-adopters. This grouping rules out the possibility of partial adoption. Some studies have considered partial adoption and model the adoption rate as a continuum of land area share using censoring methods. Such methods include the two-limit Tobit model where a double-censored error distribution is assumed (Lin, 1991), and the double hurdle model in which the two-stage decision process of whether and how much to adopt are assumed independent and sequential (Mal et al., 2012). An alternative is to model adoption at the plot level and employ Probit or Logit (Marenya and Barrett, 2007). Although partial adopters are widely observed in our survey, each plot contains either improved or local varieties, but not both. A plot-level Probit model is thus appropriate, which best reflects the plot-specific adoption decision. The plot-level Probit model also allows for heterogeneity in plot characteristics.

For each maize plot, we assume the farm household maximizes expected utility by selecting a maize variety, either improved ($T = 1$) or local ($T = 0$). Farmers are assumed to be risk averse and the plot-level expected utility U of growing maize is:

(2) $$U^T = Z^T\delta - V^T$$

where Z represents observed factors affecting U through mechanisms captured by coefficients δ, and V represents unobservables. Intuitively, utility is positively affected by maize profits, which are functions of maize yield and costs (as specified below), and negatively affected by unobserved risks. We normalize U^0, the expected utility from local varieties, to zero. The adoption rule can be written as:

(3) $$T = \begin{cases} 1, & \text{if } U^1 > 0 \\ 0, & \text{if } U^1 \leq 0 \end{cases}$$

On the production side, by specifying a suitable production function (e.g. Matuschke et al., 2007; Suri, 2011), the potential outcomes in terms of plot-level maize yield are specified in logarithmic form as (Heckman and Vytlacil, 2001):

(4a) $$y^1 = \alpha^1 + \varphi + X\beta^1 + u^1$$

(4b) $$y^0 = \alpha^0 + X\beta^0 + u^0$$

where φ is the plot-specific percentage yield gain with adoption; X is the input vector with coefficients β and u denotes unobservables. Equations (2) - (4b) jointly specify the Generalized Roy Model (Heckman and Vytlacil, 2001). Production can be expressed as $y = Ty^1 + (1-T)y^0$, or more specifically:

(5) $$y = \alpha^0 + T(\alpha^1 - \alpha^0) + T\varphi + X\beta^0 + TX(\beta^1 - \beta^0) + u$$

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

Estimation of cost changes due to adoption is empirically specified in a similar manner. In a cost function, y^T in equations (4a) and (4b) would reflect total input cost and

X is the vector of input prices together with maize output. φ would be interpreted as the plot-specific treatment effect in terms of percentage cost increase.

Estimation methods

Equation (5) is the main model to be estimated, and is applied to both yield and cost effects. Since treatment is self-determined by farmers, IV techniques are used to account for potential endogeneity. Homogeneous treatment effects are firstly assumed, i.e. all farmers increase their yields and costs by the same proportion with adoption. 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[1]. One alternative 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, equation (5) is also estimated using generalized method of moments (GMM, Hansen 1982). Finally, a generalized selection model (Heckit) is estimated via Heckman's two-stage procedure (Heckman, 1979), which provides consistent and efficient treatment effect estimates under joint normality assumption of error terms.

[1] A hierarchical IV model which differentiates plot-level and household-level characteristics has advantages such as identifying treatment effect heterogeneity and gaining efficiency (Gelman and Hill, 2007). Clustered standard errors also have potential benefits. We cluster standard errors at farm-household level in the 2SLS procedure rather than using a hierarchical model because 1) the data indicate that half of the maize growing households own only a single maize plot; and 2) a marginal treatment effect (MTE) procedure is later employed to identify treatment effect heterogeneity.

To help understand the yield effect and how it varies among heterogeneous farmers, treatment effect heterogeneity is also considered. Local instrumental variable (LIV) estimation of the marginal treatment effect (MTE) is employed to deal with such heterogeneity (Heckman, Urzua and Vytlacil, 2006). The MTE provides treatment effect estimates at each propensity-score level[2]. It is useful because it is difficult to match all covariates in all of their dimensions, especially when there are many covariates. Estimation of treatment effects across propensity scores provides the best solution. This estimation procedure has an advantage compared with hierarchical models when estimating plot-specific treatment effects as using the latter only group-specific treatment effects are identified.

Given the Generalized Roy Model in equations (2) - (4b), the MTE is defined as the treatment effect with specific realizations of X and V, $\mathrm{E}(y^1 - y^0 \mid X = x,\ V = v)$. Denote the cumulative distribution function of V as $F_V(V)$. The decision rule for adoption in equations (3) can be written as $F_V(Z\delta) > F_V(V)$, or simply $P(Z) > u^T$ where $P(Z)$ is the propensity score. It can be shown that (Heckman, Urzua and Vytlacil, 2006):

$$\text{(6)} \qquad \mathrm{E}\big(Y \mid X = x, P(Z) = p\big) = \alpha + \beta^0 x + \big(\big(\beta^1 - \beta^0\big)x\big)p + K(p)$$

where

[2] Propensity score is introduced at different evaluation levels of the LIV estimator, which differs from the propensity score matching literature in which the treatment effect as a scalar value is defined as the average difference of the variable of interest between treated and untreated observations matched by propensity score.

(7) $$K(p) = \varphi p + \mathrm{E}\left(u^1 \mid P(Z) = p\right) + p\mathrm{E}\left(u^1 - u^0 \mid T = 1, P(Z) = p\right)$$

Equations (6) and (7) lay out the basic MTE approach. Heckman and Vytlacil (2001, 2005) show that in the discrete treatment case, the MTE is equal to the local instrumental variable (LIV) estimator where the propensity is evaluated at p:

(8) $$\Delta^{LIV}\left(x, u^T\right) = \left.\frac{\partial \mathrm{E}\left(Y \mid X = x, P(Z) = p\right)}{\partial p}\right|_{p=u^T} = \Delta^{MTE}\left(x, u^T\right).$$

Computation of MTEs involves taking the partial derivative of the expected outcome, evaluated at x and p, with respect to p. Given (6) and (7), equation (8) can be written as:

(9) $$\left.\frac{\partial \mathrm{E}\left(Y \mid X = x, P(Z) = p\right)}{\partial p}\right|_{p=u^T} = x'\left(\beta^1 - \beta^0\right) + \left.\frac{\partial K(p)}{\partial p}\right|_{p=u^T}.$$

To obtain the MTE from equation (9), (β^1 - β^0) and $\partial K(p)/\partial p$ are estimated. This is a semiparametric procedure since estimation of the latter term requires nonparametric methods. The LIV algorithm proposed in Heckman, Urzua and Vytlacil (2006) is used. With estimates of $MTE(x, u^T)$, the conditional estimators of ATT, ATUT and ATE are derived as weighted averages of the MTE (Heckman and Vytlacil, 2001, 2005). For example, for the ATT:

(10) $$ATT(x) = \int MTE\left(x, u^T\right)\omega_{ATT}\left(x, u^T\right)du^T$$

where the weight is given by:

(11) $$\omega_{ATT} = \frac{\Pr\left(P(Z) > u^T \mid X = x\right)}{\int_0^1 \Pr\left(P(Z) > u^T \mid X = x\right)du^T}.$$

Finally, the unconditional estimators are derived by integrating X out:

$$ATT = \int ATT(x) dF_{X|D=1}(x). \tag{12}$$

The ATUT and ATE can be derived similarly with different weights and conditional cumulative distributions of X. Under heterogeneity, ATT, ATUT and ATE estimates are numerically different. In our case, a specific ATT is obtained for each adopting plot.

Direct changes in household income

With an assumption that maize market price does not change in the short run, the direct income effects can be computed using the estimated treatment effects, i.e. yield and cost increases due to adoption. For household i's plot k planted with an improved maize variety, the income change $\Delta\hat{I}_{ik}$ is computed as:

$$\Delta\hat{I}_{ik} = \left(PY_{ik}^{obs} - C_{ik}^{obs}\right) - \left(PY_{ik}^{*} - C_{ik}^{*}\right) = P\Delta\hat{Y}_{ik} - \Delta\hat{C}_{ik} \tag{13}$$

where P is the maize market price; (Y^{obs}, C^{obs}) and (Y^{*}, C^{*}) 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, computed using estimated treatment effects. Household-level income changes are computed as the summation across all maize plots of the household with improved maize varieties:

$$\Delta\hat{I}_{i} = \sum_{k}\left(P\Delta\hat{Y}_{ik} - \Delta\hat{C}_{ik}\right). \tag{14}$$

The counterfactual income for each adopting household is obtained by subtracting the estimated household-level income change due to adoption from observed income.

Indirect effects: Changes in markets

Following treatment effect estimation, the next step is to relate plot-level outcomes to market outcomes. Income changes by equation (14) assume that maize market price does not change, but increased supply may lower the market price received by producers and paid by consumers. The welfare impacts of supply shifts on maize market participants depend on the nature of supply and demand.

In a small open economy, price is fixed in the short run as the country is a price taker in the world market. Welfare changes occur only to adopters who increase their incomes due to the reduction in per unit cost of production. Non-adopters and pure consumers experience no change in welfare. In the closed economy, the market price decreases as total output increases, and all producers and consumers are affected (figure 1). Ethiopia was not a member state of the World Trade Organization (WTO) in 2010, and maize exports are occasionally restricted by cereal export bans (World Food Programme News, July 13, 2010). Ethiopia can be considered a relatively closed economy for maize. However, cross-border trade with neighboring countries still occurs even when cereal export bans are in effect. As a result, we assess poverty impacts of maize CGI under both a small open economy and a closed economy assumption, and the true poverty impacts will fall within the bounds of the estimates from these two cases.

In a closed economy, it is difficult to directly estimate household income changes because household demand and supply respond to the price changes and affect all maize producers and consumers. Thus, it is necessary to estimate market-level changes in prices and economic surplus, and then allocate this surplus change to appropriate households. The key parameter affecting price and economic surplus change is the cost reduction per unit of output due to improved varieties, or the *k*-shift (Alston, Norton and Pardey, 1995):

$$(15) \qquad K = \left(\frac{\hat{Y}}{\varepsilon} - \frac{\hat{C}}{1+\hat{Y}} \right) \times \text{Adoption rate}$$

where $\hat{\varepsilon}$ is the supply elasticity; $\hat{Y}$ and $\hat{C}$ are the LIV-estimated yield and cost ATTs, respectively, both computed using equations (10) - (12), with weights from equation (11).

Using the estimated *k*-shift, the counterfactual output price level is retrieved. As shown in figure 1, the idea is to derive backwardly from the observed equilibrium price at *b* (P^{obs}, Q^{obs}) the counterfactual equilibrium price at *a* (P^{ct}, Q^{ct}). Mathematically, it can be shown that the counterfactual equilibrium price can be obtained using equation (16):

$$(16) \qquad P^{ct} = P^{obs}(\varepsilon + \eta)/(\varepsilon + \eta - K\varepsilon)$$

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, Norton and Pardey, 1995), where Z equals the relative reduction in prices, $(P^{ct} - P^{obs})/P^{ct}$:

$$(17) \qquad \Delta PS = P^{ct}Q^{ct}(K - Z)(1 + 0.5Z\eta)$$

$$(18) \qquad \Delta CS = P^{ct}Q^{ct}Z(1 + 0.5Z\eta)$$

Producer and consumer surplus changes are allocated to individual households. On the demand side, only maize buyers experience consumer surplus changes. Thus, we allocate ΔCS to surveyed 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. Welfare impacts vary by household net sales position. We first decompose the aggregate producer surplus change into yield and price effects:

$$\Delta PS = \Delta PS_{yield} + \Delta PS_{price} \qquad (19)$$

where ΔPS_{price} is equal to $-P^{ct}Q^{ct}Z(1+0.5Z\eta)$ which has an absolute value that numerically equals ΔCS, and ΔPS_{yield} is the difference between ΔPS and ΔPS_{price}. ΔPS_{price} is allocated to all maize sellers based on their market shares since only sellers suffer from the price drop. All adopting plots, however, observe productivity and cost changes. Thus, ΔPS_{yield} is first allocated to all adopting plots (which have different yield and cost MTEs) based on their shares of yield gains weighted by plot-level profitabilities (see table 1 for details), and then aggregated to households. This procedure accounts for partial adoption, direct benefits from adoption, and indirect effects from market price change. The counterfactual household income of each household is computed by subtracting the income change due to allocation from the observed household income, and the counterfactual income distribution is mapped.

Poverty impact estimation

Under both the small open economy and closed economy assumption, the counterfactual income distribution is derived using procedures described above. Foster-Greer-Thorbecke (FGT) poverty indices (Foster, Greer, and Thorbecke, 1984) are then calculated for a given poverty line using the observed and counterfactual incomes. The poverty impacts, in terms of reductions in poverty headcount ratio, depth, and severity are measured as the differences of the respective poverty indices.

Data and Results

The data come from a household survey conducted jointly by CIMMYT and EIAR during 2009-2010. Four regions are covered: Oromia, Amhara, Tigray, Southern Nations, Nationalities, and People's Region (SNNPR), which together account for more than 93% of maize production in Ethiopia (Schneider and Anderson, 2010). The survey uses a stratified random sampling strategy that includes interviews with farmers from 30 woredas[3] across these regions. A total of 1,396 farm households were surveyed, of whom 1,359 grew maize on a total of 2,496 plots. Plot areas were reported by farmers and details of crop production such as varieties, yields, and inputs were gathered as recall data from the previous cropping season[4].

[3] A woreda is an administrative district, comparable to a United States county.

[4] Beegle, Carletto and Himelein (2012) show that agricultural data collected in this manner are generally of good quality.

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 years. Many OPVs are developed for challenging conditions (i.e. droughts, pests) and under circumstances where seed markets are underdeveloped or missing. Whatever varieties farmers grow, inbred lines are crossed through open pollination. Thus, varieties are only differentiated as being either improved or local[5]. Any hybrid that has been ever recycled or OPV that has been recycled for more than three seasons is categorized as local[6]. After accounting for sampling weights, our data suggest an adoption rate of 39.1% by area.

Farmers tend to adopt improved varieties on larger, flatter plots and closer to their homes (table 2). Among the 1,359 households, there are 503 adopters, 583 non-adopters,

[5] There are several reasons for this categorization. First, the pollination process is not controlled for and varieties may cross with each other if the plots are close to each other. Second, OPVs are a collection of varieties with different characteristics such as drought tolerance and pest resistance (Pixley and Bänziger, 2004). As 2010 was a good cropping year, specific yield advantages of OPVs are hardly realized and difficult to identify. Third, the mean per-hectare yields of hybrids and OPVs in our data differ only with 10% significance. See Figure 2 for the kernel density estimations of yields of the three maize varieties.

[6] This cut-off is suggested by local experts.

and 273 partial adopters (table 3). Larger and wealthier land holders[7] with more family members tend to adopt improved maize 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.

Farmers grow improved varieties during the long rainy season (mid-June to mid-September) more frequently than during the short rainy season (February-April, see table 4). Inputs such as oxen power, fertilizer, and other inputs reported in monetary terms, including purchased seeds and pesticides, are significantly higher for adopting plots. Labor use does not vary by variety. Improved varieties yield about 1275 kg more dry maize[8] per hectare than local varieties, a 59.0% yield difference.

Estimating treatment effects

In order to identify the treatment effects with endogenous adoption, IV techniques are employed. The IVs should affect adoption, but only affect the outcome through their impacts on adoption. Similar procedures are used for yield and cost estimation.

In the yield ATT estimation, five potential IVs are used: the distances to the nearest seed dealer, agricultural extension office, farmer cooperative and main market, as well as the quality of roads to the main market. These IVs reflects the accessibility of improved seeds and markets, extension efforts, availability of credit and business services, and

[7] Total household wealth is computed as the sum of the self-reported values of all household assets.

[8] All maize yields have been converted to dry maize throughout the article in a manner suggested by local experts.

degree of commercialization. All these IVs directly affect farmer's adoption decision, but not yield. Specifically, closer distances to facilities and markets and better roads are likely to be positively correlated with adoption, which should be the only channel which they are related to maize yield.

Besides adoption, other variables included in the production function (equation 5) are per-hectare inputs (labor days, ox plowing days, amount of fertilizer and other capital inputs, all in logarithmic form)[9], 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 self-reported discrete scales), season (short or long), village altitude, and regional dummies. The combination of the five IVs are tested in 2SLS and GMM environments, and stands a series of tests with respect to endogeneity, under-identification, over-identification and weak identification[10].

A Cobb-Douglas production function is estimated via 2SLS, Probit-2SLS, GMM and Heckit procedures to reveal yield ATT, or $\hat{Y}$. Alternative estimates under heterogeneity are obtained by taking weighted averages of MTEs, as described previously. As reported in the upper panel of table 5, these results are numerically close. Across different models, $\hat{Y}$ is estimated to be between 47.6% - 63.3%. As a robustness check, a flexible translog

[9] Following Jacoby (1993), a constant of one is added to all inputs that have zero observations, which, as explained in his article, does little harm to the robustness of estimates.

[10] Detailed test results are available upon request.

functional form is employed, and $\hat{Y}$ is estimated as 55.1% - 61.6%. This closeness builds confidence in the estimates. Another means of robustness check is implemented: estimation of $\hat{Y}$ using propensity score matching at the plot-level. Three matching techniques are employed, including nearest neighbor matching, radius matching, and kernel matching. The yield effect is estimated to be 43.4% - 48.9% (all with 1% significance), numerically close to the regression estimates.

Finally, the treatment effect is estimated using the subsample of 273 partial adopters with 772 plot-level observations. The treatment effect is estimated as the difference in productivity between improved and traditional plots of the same farm household. The model is specified as the differences between equations (4a) and (4b):

$$\Delta y_{ikl} = \varphi + \beta_{kl} \Delta X_{ikl} + \Delta u_{ikl} \tag{20}$$

where the difference is taken between the plot k (improved) and plot l (local) for the i^{th} 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 both observed and unobserved household-level heterogeneity and identifies the treatment effect as the constant φ. OLS regressions of Cobb-Douglas and translog specifications suggest 38.7% and 42.1% yield increases, respectively, both significant at 5%. These results are very close to the observed per-hectare yield difference for partial adopters (43.3%) and other robustness check estimates, and lend credence to our estimates.

Estimated yield MTEs are highest among mid-low propensity scores, as observed using both Cobb-Douglas (figure 3a) and translog function form (figure 3b). These results may indicate negative selection: farmers are less likely to grow improved varieties on plots that are more likely to observe a higher yield gain, a pattern also found in Suri (2011). About half of the households surveyed grow maize only on a single plot, and negative selection indicates that farmers planting maize on plots with higher yield potential may be more conservative. As a test for heterogeneity in $\hat{Y}$, 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 were negative and significant at 1% level, confirming the existence of heterogeneity.

The cost ATT, or $\hat{C}$, is estimated in a similar manner. However, only three of the five IVs are included in the cost effect estimation: distances to the nearest extension office, farm corporative and seed dealer, which are not supposed to correlate with total cost per hectare other than through adoption. Distance and quality of road to the main market are excluded as they reflect the degree of commercialization and may be correlated with input prices, including improved seeds. Other variables include the prices of different inputs (labor, fertilizer, ox plow, pesticides), maize yield per hectare, maize area, plot and household characteristics, and regional dummies. These three IVs pass tests of endogeneity, under-identification, over-identification and weak identification.

Following Jacoby (1993), shadow prices of labor and ox plow are computed from production function estimation and employed here. Results are reported in the lower panel of table 5). Assuming a homogeneous treatment effect, $\hat{C}$ is estimated to be 22.8% - 29.4% under a Cobb-Douglas specification and 23.1% - 27.4% under a translog specification. The LIV estimates are close, reporting 27.8% and 25.3% cost increases due to additional inputs. Propensity score matching as another robustness check suggests a per hectare cost reduction of 22.1% - 25.6% (with at least 5% significance).

Although the first-difference type procedure in equation (20) does not apply to cost function estimation, as the same household cannot differentiate input prices among plots, we compute the difference in average per-hectare total input cost difference between improved and local maize varieties using plot-level data. Shadow prices for labor and ox plow used when growing improved maize varieties indicate an average 30.2% increase in input cost per hectare among all plots, the increase being even higher among the plots of partial adopters (33.4%). All robustness checks support the econometric estimates.

Estimated cost MTEs generally decrease as propensity scores increase, with either the Cobb-Douglas (figure 4a) or translog (figure 4b) functional form. Similar OLS 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: farmers are less likely to adopt improved maize varieties given high additional costs even if the yield potential is high. Given the existence of heterogeneity in both yield and cost MTEs, the LIV estimates are now presented.

Estimating the counterfactual price in the closed economy

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 estimates of 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 of both maize supply and demand were obtained from existing literature[11].

The literature suggests a wide variation of estimates of elasticity of maize supply in Sub-Saharan Africa, ranging from 0.157 to 0.68 (Kiori and Gitu, 1992; Cutts and Hassan, 2003; Abrar, Morrissey and Rayner, 2004; Omamo et al., 2007; Alene et al., 2008). We assume the supply elasticity to be 0.5 as it is comparatively easy for farmers to switch in and out of maize production. Examples of demand elasticity estimates include Bezuneh, Deaton and Norton (1988) who report -1.19 for maize and beans for Baringo, Kenya; Jayne, Lupi and Mukumbu (1995) who report -1.41 for Nairobi, Kenya, and Omamo et al. (2007) who report -0.53 for Kenya, Ethiopia and Uganda. We use a unit absolute value of

[11] We conduct a sensitivity analysis on these and other parameters, as detailed below.

demand elasticity.

The market price P^{obs} is obtained as a six-year average (2005-2010) of national-level annual producer prices from FAOSTAT, which is 0.220 US dollar per kilogram[12]. With P^{obs}, and sample-level Q^{obs}, the k-shift is computed as a 39.1% cost reduction per kilogram of maize. A P^{ct} of 0.253 US dollars per kilogram is obtained by averaging the LIV estimates from the Cobb-Douglas or translog technologies[13]. The aggregate producer surplus and consumer surplus changes are USD 99,554 and USD 49,777 among the surveyed households, respectively; 6.37% of the latter is allocated to these households according to their maize consumption share of total supply. Plot-level yield and cost MTEs are used to derive counterfactual incomes. 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 274.47 million and 137.23 million, respectively.

Assessing poverty impacts

The counterfactual and observed income distributions are used to measure poverty. Three poverty lines are employed: \$1, \$1.25 and \$1.45 per person per day, which roughly represent a 95% confidence interval for the mean poverty line for the poorest 15 countries including Ethiopia (see Chen and Ravallion, 2010). We compute poverty impacts using MTEs and LIV-estimated ATTs.

[12] Producer price is used here as retail price observes larger variation across areas and relative statistics are limited.

[13] The two counterfactual prices are numerically very close; thus the average should be acceptable.

All three poverty indices decrease following adoption of improved maize varieties (table 6). Impacts on the poverty headcount reduction is slightly larger under the assumption of a small open economy, where the poverty headcount ratio dropped by 1.0 - 1.3 percentage points, as compared to 0.7 - 0.9 percentage points in the closed economy. This makes sense since the profitability of maize decreases as market price drops, and only a small portion of total consumer surplus is enjoyed by surveyed households. These numbers further imply that 1.8% - 3.3% of the poor have escaped poverty in the current year due to the adoption of improved maize[14]. Other estimates under different assumptions of economic openness are similar. Specifically, a 2.3% - 2.7% decrease in poverty depth and a 2.9% - 4.3% decrease in poverty severity are observed. These results are robust across all poverty lines.

To explore the distribution of impacts, the variations in producer benefits from adoption of improved maize varieties along the counterfactual income levels are presented in figure 5, estimated by local polynomial regressions (consumer benefits are small). Poor adopters benefit the least assuming either economic openness. Analysis shows that the poor are as likely to adopt as the non-poor, and their yield and cost MTEs

[14] 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 .2994 and .0100, respectively. Thus, the percentage of the originally poor who have escaped poverty is computed as .0100 / .2994 = .0334, or 3.3%. Similar computations with respect to poverty depth and severity are applied.

are generally similar. Limited land area, rather than an inability to adopt, explains why the poor receive relatively few producer benefits[15].

Sensitivity analyses of the poverty impact estimates are conducted, and suggest that the estimates are robust (see Appendix for details). The estimate of a 0.7 - 1.3 percentage reduction in poverty implies that 0.48 - 0.89 million people in rural Ethiopia who otherwise would have been poor are not due to the adoption of improved maize varieties.

Concluding Remarks

Crop genetic improvement in maize has had substantial impacts on poverty in rural Ethiopia. Such poverty impacts should increase over time as maize area and maize consumption expand. Given the cross-sectional data, poverty impacts were only estimated for the current year. It is likely that such impacts have been felt over several years as improved maize varieties were continually released. The results are consistent across alternative poverty lines and estimation strategies. Multiple robustness checks were conducted and consistently support our findings. Most of the reduction in poverty among maize producers comes through producer benefits, but consumer gains over the whole economy are also large. Since total consumer gains are spread over a large number of households, most of whom were not represented in the survey, this study understates the true magnitude of poverty reduction from maize CGI. Although the overall impact is

[15] Further computation shows that the mean differences of maize areas between the poor and non-poor are significantly different under each of the five poverty lines.

substantial, poor producers benefit less than the non-poor producers (in absolute terms) from maize CGI because they have less land than the non-poor.

The combination of treatment effect and economic surplus analysis allows us to estimate both direct and indirect effects on household well-being of technology adoption. This approach is an improvement over typical economic surplus applications which use *k*-shifts derived from expert opinion or from experimental-trial data without accounting for household-specific heterogeneity. Treatment effect estimation could be combined with more general multi-market and general equilibrium models. It could also be adapted to more general cases where distributional impacts are of interest to provide information for research planners and policy makers.

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Table 1. Household Welfare Changes with Improved Maize Varieties by Net Sales Position

Market role			Maize utilization[1,2]									Overall welfare effect[3]
			Self-produced consumption			Purchased consumption			Selling			
			ΔPS_{yield}	ΔPS_{price}	ΔCS	ΔPS_{yield}	ΔPS_{price}	ΔCS	ΔPS_{yield}	ΔPS_{price}	ΔCS	
Maize grower	Adopter	Pure seller							+	-	0	?
		Self-sustainer	+	0	0							+
		Net seller	+	0	0	0	0	+	+	-	0	?
		Net buyer	+	0	0	0	0	+	+	-	0	+
	Non-adopter	Pure seller							0	-	0	-
		Self-sustainer	0	0	0							0
		Net seller	0	0	0	0	0	+	0	-	0	-
		Net buyer	0	0	0	0	0	+	0	-	0	+
Pure buyer						0	0	+				+

[1] Grey cells indicate the group of households does not participate. Net sellers do not necessarily purchase maize in the market; similarly, net buyers do not necessarily sell maize.

[2] Partial adopters are considered as both adopters (for adopting plots) and non-adopters (for non-adopting plots). 1) ΔPS_{yield} is allocated to all adopters according to the shares of their estimated yield increases of aggregate yield increases; 2) ΔPS_{price} is allocated to all maize sellers according to their market shares; and 3) ΔCS is allocated to all buyers based on the households' share of purchased maize among the total market supply.

[3] For the two undetermined cases, i.e. pure sellers and net sellers among adopters, although it is likely that ΔPS_{yield} is large enough to offset the negative term of ΔPS_{price}, the total welfare effect can still be negative, especially when the yield gain is small.

Table 2. Descriptive Statistics of Plot Characteristics

	Improved[1] (n = 1214)	Local[1] (n = 1282)	Difference[2]
Altitude (meters)	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 (.000)
Plot area (ha)	.453 (.416)	.334 (.357)	.119 (.000)
Soil slope (1-3: gentle-medium-steep)	1.43 (.65)	1.52 (.70)	-.11 (.002)
Soil depth (1-3: shallow-medium-deep)	2.21 (.84)	2.17 (.85)	.05 (.162)
Soil fertility (1-3: good-average-poor)	2.45 (.62)	2.47 (.60)	-.02 (.359)

[1] Standard deviations are in parentheses.

[2] p-values of t-tests of differences by maize varieties are in parentheses.

Table 3. Descriptive Statistics of Maize Households by Adoption Type[1]

	Adopters (n = 503)	Non-adopters (n = 583)	Partial-adopters (n = 273)
Total cultivated area (ha)	2.02 (1.51)	1.86 (1.33)	2.37 (1.89)
Total maize area (ha)	.709 (.674)	.553 (.545)	1.090 (1.173)
Household size	6.58 (2.46)	6.29 (2.21)	6.91 (2.40)
Total household wealth[2] (thousand Ethiopian birrs)	18.83 (35.31)	13.18 (29.51)	22.69 (61.18)
Poverty rate by household (< 1.25 USD / person day)	40.36%	46.14%	39.93%
Head gender (% of male)	.950 (.218)	.913 (.283)	.981 (.134)
Head age (years)	42.01 (12.95)	43.90 (12.52)	43.15 (11.34)
Head marital status (proportion married)	.946 (.226)	.906 (.293)	.967 (.179)
Head education (years)	2.92 (3.36)	2.48 (2.99)	2.99 (3.32)
Head literacy rate[3]	.451 (.492)	.408 (.498)	.418 (.494)

[1] Standard deviations are reported in parentheses.
[2] Computed as the sum of the self-reported values of all household assets. The daily average exchange rate in 2010 is 1 USD = 14.38 ETB.
[3] Defined as at least some education, as opposed to no education at all.

Table 4. Descriptive Statistics of Maize Cropping Practice

	Improved[1] (n = 1214)	Local[1] (n = 1282)	Difference[2]
Season (1 = long; 0 = short)	.945 (.228)	.915 (.279)	.030 (.003)
Intercropping (1 = yes; 0 = no)	.129 (.266)	.173 (.384)	-.044 (.135)
Labor days per ha	105.0 (115.4)	102.9 (78.5)	2.1 (.588)
Ox plow days per ha	8.01 (7.87)	4.92 (4.63)	3.09 (.000)
Fertilizer (kg per ha)	150.6 (243.3)	56.3 (305.8)	94.3 (.000)
Other inputs per ha[3] (Ethiopian birrs[4])	299.1 (398.9)	67.7 (210.8)	231.4 (.000)
Yield (kg per ha)	3434.9 (2176.2)	2159.6 (1610.8)	1275.2 (.000)

[1] Standard deviations are reported in parentheses.
[2] p-value of t-tests are reported in parentheses.
[3] Including cost for seeds purchased and pesticides.
[4] The daily average exchange rate in 2010 is 1 USD = 14.38 ETB.

Table 5. **ATT Estimation of Yield and Cost Effects**[1]

ATT	Model specification	Homogeneity				Heterogeneity
		2SLS	Probit-2SLS	GMM	Heckit	LIV
Yield effect	Cobb-Douglas	.588 (.170)	.476 (.128)	.561 (.145)	.496 (.129)	.633 (.242)
	Translog	.616 (.170)	.564 (.126)	.594 (.146)	.551 (.128)	.535 (.203)
Cost effect	Cobb-Douglas	.276 (.113)	.228 (.084)	.261 (.102)	.294 (.093)	.278 (.110)
	Translog	.243 (.097)	.231 (.089)	.239 (.110)	.274 (.095)	.253 (..098)

[1] Standard errors of the treatment effects are reported in parentheses; LIV standard errors are obtained by bootstrapping 100 times.

Table 6. Poverty Impacts of Improved Maize Varieties

	Observed	Small Open Economy	Poverty impact[1]	Closed Economy	Poverty impact[1]
$1 per person per day					
Headcount	.2894	.2994	.0100	.2966	.0072
Depth	.0963	.0989	.0026	.0990	.0027
Severity	.0435	.0452	.0017	.0449	.0014
$1.25 per person per day					
Headcount	.4162	.4291	.0129	.4255	.0093
Depth	.1496	.1534	.0038	.1537	.0041
Severity	.0724	.0746	.0022	.0751	.0027
$1.45 per person per day					
Headcount	.4957	.5079	.0122	.5050	.0093
Depth	.1947	.1995	.0048	.1992	.0045
Severity	.0983	.1027	.0044	.1024	.0041

[1] All poverty impacts are reported as percentage point changes (the post-adoption compared to the counterfactual baseline).

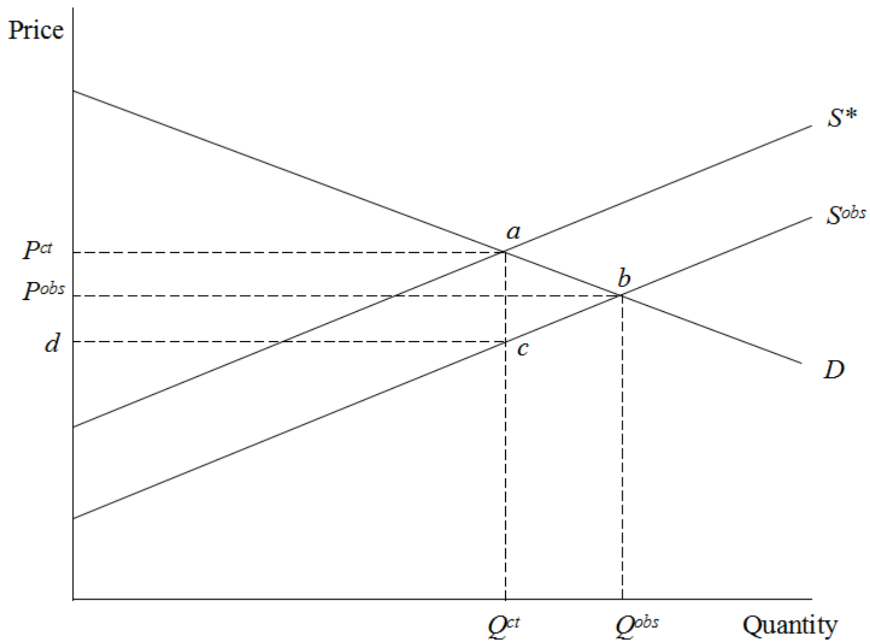


Fig. 1. Economic surplus change in a closed economy

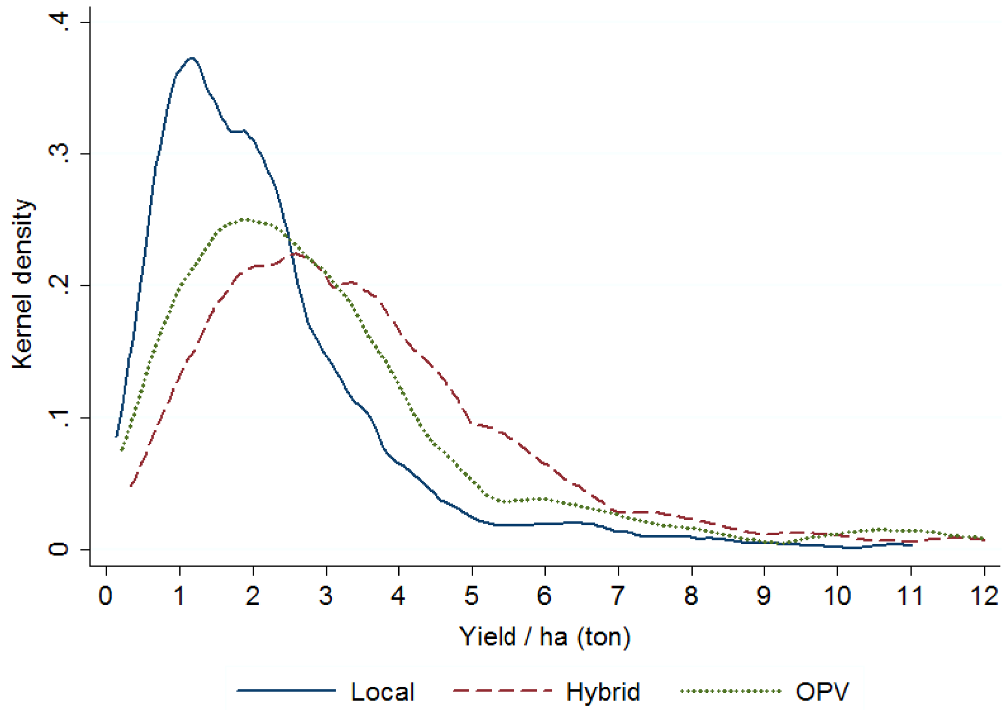
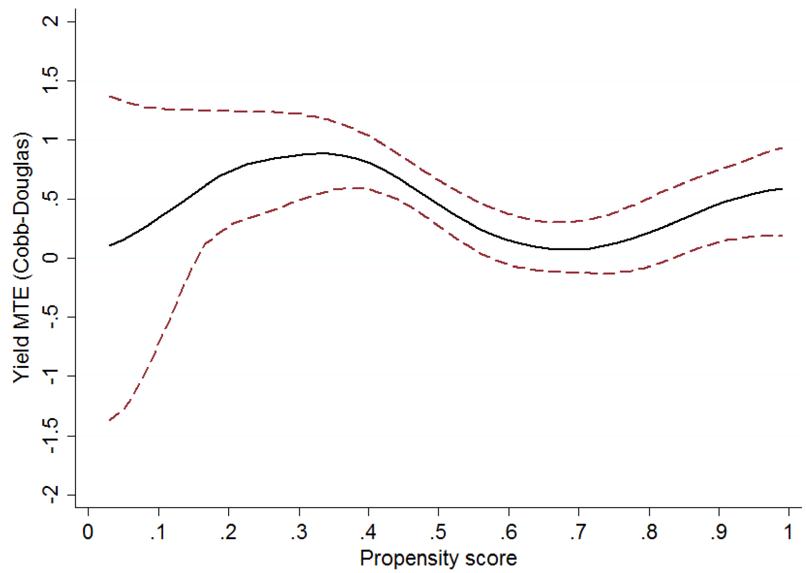
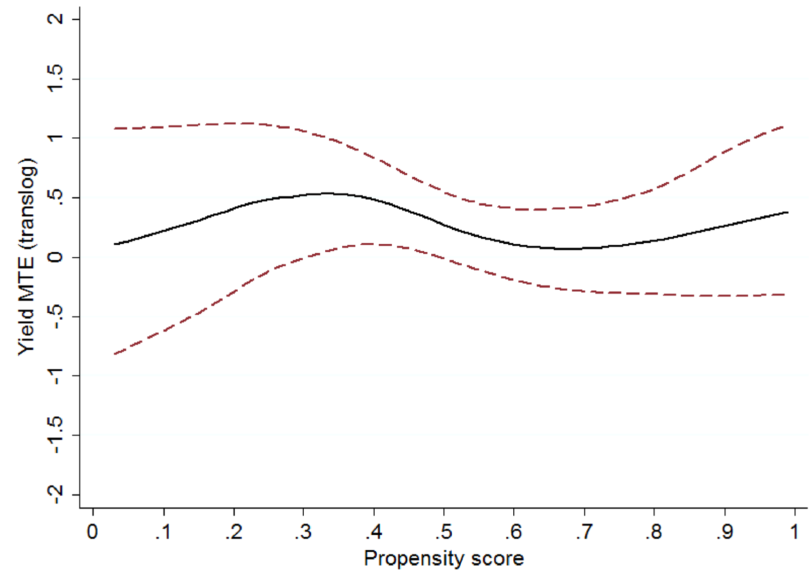


Fig. 2. The kernel density estimates of yields of different maize varieties



(a)



(b)

Fig. 3. Yield MTE using semiparametric LIV estimator[1]

[1] Estimated using local polynomial regression. Solid line shows the estimated MTE; dashed lines are 95% confidence intervals obtained via bootstrapping.

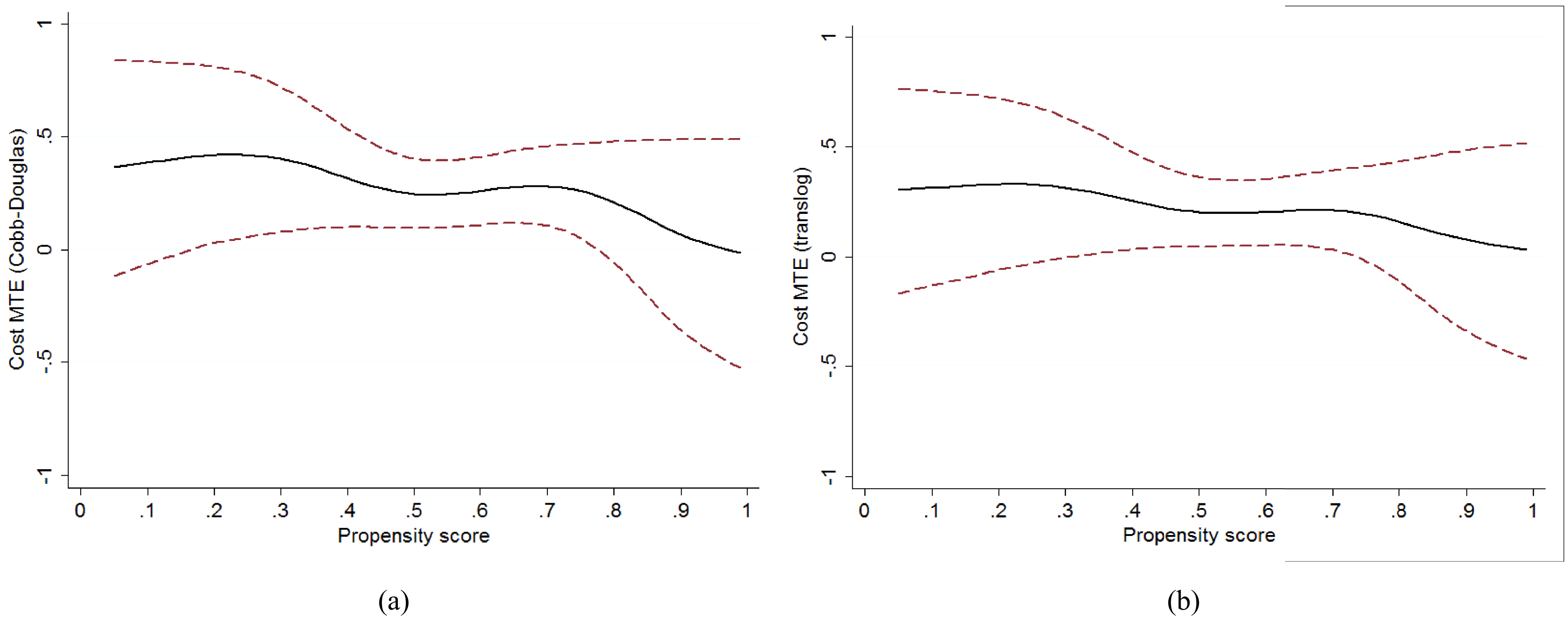


Fig. 4. Cost MTE using semiparametric LIV estimator[1]

[1] Estimated using local polynomial regression. Solid line shows the estimated MTE; dashed lines are 95% confidence intervals obtained via bootstrapping.

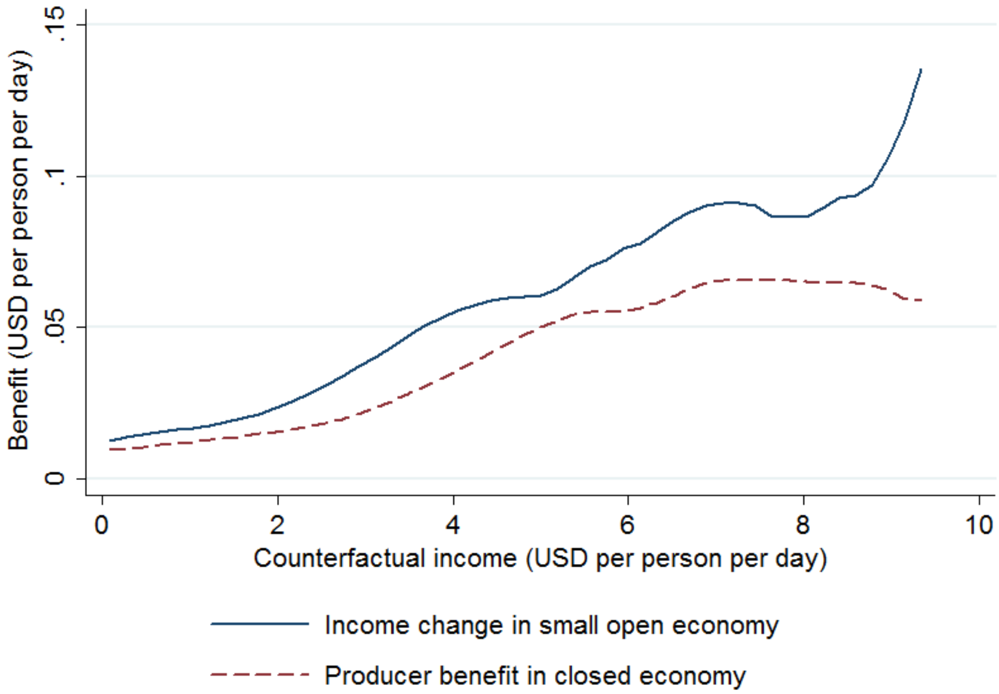


Fig. 5. Benefits due to adoption across counterfactual income levels[1]

[1] 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.

Appendix: Sensitivity Analysis of Poverty Impacts

As a means of robustness check, sensitivity analyses were conducted for the poverty impact estimates. Variations in several parameters can alter the poverty impact estimates. These parameters include *ATT*s ($\hat{Y}$ and $\hat{C}$), ε, η, the adoption rate, and the proportion of maize supply purchased by rural households. The first two are econometrically estimated; while the last four are obtained from previous literature or algebraically computed. Different combinations of these parameters affect the estimates of the *k*-shift, P^{ct}, the total producer and consumer surplus change to be allocated, and the counterfactual household income. Poverty impacts via FGE indices were computed as:

$$\text{(A1)} \qquad \frac{1}{n}\sum_{i=1}^{q^{ct}}\left(\frac{z-I_i^{ct}}{z}\right)^{\alpha}-\frac{1}{n}\sum_{i=1}^{q^{obs}}\left(\frac{z-I_i^{obs}}{z}\right)^{\alpha}$$

Randomness exists in both the counterfactual household income, I_i^{ct}, and the counterfactual number of poor people, q^{ct}, which is determined by the former. The observed and counterfactual household incomes are linked via the estimated income change due to adoption, ΔI_i:

$$\text{(A2)} \qquad I_i^{ct}+\Delta I_i=I_i^{obs}$$

Thus, variations in the parameters above affect I_i^{ct} via ΔI_i.

For the econometrically estimated parameters, a 95% confidence interval of the estimated mean is obtained via bootstrapping. Also, the adoption rate is assumed to vary by as much as 20 percentage points, i.e. from 19.1% to 59.1%. The proportion of maize supply purchased by rural households is allowed to vary from 5% to 20%. Based on literature estimates, the value of ε and the absolute value of η are assumed to vary from 0.2 to 1 and 0.5 to 1.5, respectively.

The results of the sensitivity analysis of the poverty impact estimates for small open and closed economies are reported in table A1. Joint variation of six parameters is allowed and the global maximum and minimum of equation (A1) is solved, which should be the upper and lower bounds even when all parameters are realized at their maximum values. The variation of parameters leads to noticeable variation in poverty impacts, with changes mainly being upward. For example, compared with the poverty headcount ratio of 0.7 - 1.3 percentage point reduction, the estimates vary 0.4 - 3.5 percentage points. All three FGT indices are consistently higher.

Table A1. Sensitivity Analysis of Estimated Poverty Impacts

	Small open economy			Closed economy		
	Poverty impact[1]	Lower bound	Upper bound	Poverty impact[1]	Lower bound	Upper bound
$1 per person per day						
Headcount	.0100	.0036	.0301	.0072	.0036	.0279
Depth	.0026	.0011	.0098	.0027	.0014	.0103
Severity	.0017	.0008	.0121	.0014	.0008	.0095
$1.25 per person per day						
Headcount	.0129	.0050	.0358	.0093	.0044	.0322
Depth	.0038	.0016	.0155	.0041	.0019	.0167
Severity	.0022	.0013	.0146	.0027	.0014	.0163
$1.45 per person per day						
Headcount	.0122	.0057	.0308	.0093	.0050	.0294
Depth	.0048	.0023	.0240	.0045	.0021	.0246
Severity	.0044	.0020	.0261	.0041	.0023	.0233

[1] Computed as the difference in percentage point change between the observed and counterfactual measures.