Three Essays on Adoption and Impacts of Improved Maize Varieties in Ethiopia

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ABSTRACT

Public agricultural research has been conducted in Africa for decades and has generated numerous crop technologies, while little is understood on how agricultural research affects the poor and vulnerable groups such as children, and how farmers' perceptions affect their adoption decisions. This dissertation helps fill this gap with three essays on adoption and impacts of improved maize varieties in rural Ethiopia.

The first essay estimates poverty impacts. Field-level treatment effects on yield and cost changes with adoption are estimated using instrumental variable techniques, with treatment effect heterogeneity fully accounted for in marginal treatment effect estimation. A backward derivation procedure is then developed within an economic surplus framework to identify the counterfactual income distribution without improved maize varieties. Poverty impacts are estimated by exploiting the differences between the observed and counterfactual income distributions. Improved maize varieties have led to 0.8-1.3 percentage drop in poverty headcount ratio and relative reductions in poverty depth and severity. However, poor producers benefit the least from adoption due to their small land holdings.

The second paper assesses the impacts on child nutrition outcomes. The conceptual linkage between maize adoption and child nutrition is first established using an agricultural household model. Instrumental variable (IV) estimation suggests the overall impacts to be positive and significant. Quantile IV regressions further reveal that such impacts are largest among the most severely malnourished. By combining a

decomposition procedure with estimates from a system of equations, it is found that the increase in own-produced maize consumption is the major channel such impacts occur.

The third paper explores how farmers' perceptions of crop traits affects their willingness to adopt improved maize varieties. Under a random utility framework, a mixed logit procedure is implemented to model farmer's adoption intention, where perceptions of key varietal traits are first identified, and then instrumented using a control function approach to account for potential endogeneity. Perceived yield is found to be the most important trait affecting farmers' adoption intention. Further, yield perceptions among previous adopters appear to be affected by within-village peer effects rather than the real crop performance.

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Chapter 1

Introduction

Policy makers are increasingly interested in understanding impacts of interventions on social objectives. Public agricultural research has been conducted in Africa for several decades, which has generated numerous crop technologies diffused and adopted for many years. While many studies have examined the aggregate impacts of agricultural research, little work has been done on how agricultural research affects the poor, as well as child nutrition status. Also, though previous studies have extensively investigated factors that affect the adoption of agricultural technologies, few have focused on the role of farmers' perceptions of technology traits on adoption decision making. This dissertation helps fill this gap through empirical investigations of these issues.

Maize is among the most important food and cash crops in Ethiopia. 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 the impacts on vulnerable groups such as the poor and children. Also, little is known about how farmers' perceptions affect their adoption decisions. These important but not well understood topics are the focus of this dissertation which includes three essays on adoption and impacts of improved maize varieties in rural Ethiopia.

The first essay estimates ex-post impacts of improved maize varieties on poverty for rural Ethiopia. The paper uses a treatment effect approach to estimate field-level yield and cost effects. It employs instrumental variables and marginal treatment effect techniques to examine impacts under assumptions of homogeneous and heterogeneous treatment effects. A backward derivation procedure is then developed within an economic surplus framework to identify the counterfactual income distribution that would have existed without improved maize varieties. Poverty impacts are estimated by exploiting the differences between the observed and counterfactual income distributions. Improved maize varieties in rural Ethiopia have led to 0.8-1.3 percentage drop in poverty headcount ratio and relative reductions in poverty depth and severity. However, poor producers benefit the least from adoption due to their small land holdings.

The second essay assesses the impacts of the adoption of improved maize varieties on child nutrition outcomes in rural Ethiopia. The conceptual linkage between adoption of improved maize varieties and child nutrition is first established using an agricultural household model. Instrumental variable (IV) estimation suggests the overall impacts of adoption on child height-for-age and weight-for-age z-scores to be positive and significant. Quantile IV regressions further reveal that such impacts are largest among children with the worst nutritional outcomes. By combining a decomposition procedure with estimates from a system of equations, it is found that the increase in own-produced maize consumption is the major channel through which adoption of improved maize varieties affects child nutrition.

The third essay switches attention from impact evaluation to adoption decision making, exploring how perceptions of crop traits affects farmers' willingness to adopt improved maize varieties in rural Ethiopia. A random utility framework is first established that incorporates farmers' perceptions into adoption decision making. A mixed logit procedure is implemented to model farmer's adoption intention, where perceptions of key varietal traits are first identified, and then instrumented using a control function approach to account for potential endogeneity. Perceived yield is found to be the most important trait affecting farmers' adoption intention. Further, yield perceptions among previous adopters appear to be affected by within-village peer effects rather than the objective varietal performance that the farmer experiences. Several policy implications for adoption promotion conclude the paper.

Chapter 2

Essay1: Impacts of Improved Maize Varieties on Poverty in Ethiopia

2.1. 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 produced for many of the world's agro-ecologies and spread through agricultural extension efforts. These technologies have 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, relatively few empirical 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.

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 Sub-Saharan Africa beyond their impacts on productivity, profitability and basic economic surplus (Seyoum et al., 1998; Manyong et al., 2003; Alene and Hassan, 2006).

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This article bridges this gap through the development and application of a new procedure to assess poverty impacts of CGI in Ethiopia. We employ a recent household survey to empirically assess how adoption of improved maize varieties has contributed to poverty reduction among maize producers in rural Ethiopia. We build this analysis from the plot-level to the household and the market. At the plot-level, the treatment effect 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 to aggregate impacts to the market and examine how the varieties have changed market prices and aggregate economic surplus. 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. This limited impact means it is necessary to identify complementary polices and investments to alleviate poverty among poor producers.

2.2. Technology adoption and impact measurement

2.2.1. 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. As household-level changes in the unit cost of production are aggregated over many adopters, indirect effects emerge at the market-level, and market prices may decline due to increased supply. These changes benefit consumers, but adversely affect producers, especially those who fail to adopt. Despite these confounding effects, a large literature links CGI research to positive aggregate economic impacts in SSA (Alston et al. 2000; Maredia et al., 2000; Alene and Coulibaly, 2009; 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; Mills, 1997; Karanja et al., 2003), 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.

2.2.2. Treatment effects and agricultural technology impacts

Plot-level impacts of agricultural technology can be considered as treatment effects, where the treatment is technology adoption, a decision made by the farmer. Most treatment effect analyses using observational data are based on the potential outcomes framework (Rubin, 1974), where each observational unit has a potential outcome in the treated and untreated state. 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); then 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):

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

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 (self-made decision to adopt technology) is non-random.

Strategies are needed to eliminate selection bias and identify the treatment effect under this endogeneity, with propensity score matching (PSM, Mendola, 2007; Becerril and Abdulai, 2010; Kassie et al., 2011) and instrumental variable (IV) techniques (Matuschke et al., 2007; Minten and Barrett, 2008; Dercon et al., 2009) 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, this assumption can be violated as unobservable confounders such as farmer's motivation, risk attitude, social network and price expectations are likely to affect adoption. Violation of this assumption leads to biased results. 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 structure of the cause-effect relationship and about the correlations between treatment participation and outcomes. Specifically, 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 need to be carefully considered when measuring the direct impacts of technology adoption. These differences, or treatment effect heterogeneity, can vary with observed and unobserved characteristics at the plot (e.g. fertility) and household level (e.g. managerial capability). Recent literature on treatment effect heterogeneity 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 non-decreasing 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.

2.3. Modeling procedure

2.3.1. Treatment effect estimation

Most empirical assessments of CGI impacts classify households as either adopters or non-adopters (Mendola, 2007; Becerril and Abdulai, 2010; Kassie et al., 2011). However, this classification fails to consider partial adopters who adopt improved varieties only on some of their plots (Smale et al., 1994). Some studies model partial adoption as a rate or a continuum of land share using censoring methods. Such 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. An alternative is to model adoption at the plot level and employ probit or logit model (Marenya and Barrett, 2007). Although partial adopters are widely observed in our survey, each plot contains either improved or local varieties, but not both. Thus, land plots are appropriate basic units of our econometric modeling.

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:

$$y = \alpha + T\varphi + X\beta + u \tag{4}$$

Estimation of equation (4) quantifies the yield advantage of improved maize varieties as the coefficient φ of the treatment indicator T.

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:

$$C = \lambda + T\theta + P\gamma + v \tag{5}$$

In equations (5), C 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 v denotes unobservables. Capital cost is not accounted for in the short-run analysis. The parameter θ is interpreted as the plot-specific treatment effect in terms of percentage cost increase due to adoption.

Equations (4) and (5) 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. For baseline estimation, homogeneous treatment effects are 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. 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, equations (4) and (5) are 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 for each plots. Use of a propensity score is useful since it is difficult to match covariates in all of their dimensions, especially with many covariates. 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 proposed in Heckman et al. (2006). 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).

2.3.2. 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 and does not change with increased domestic supply. Adopters experience direct welfare effects and no indirect effects occur. In a closed economy, indirect effects also occur due to supply-induced drops in maize prices 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 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 (WTO) where maize exports are occasionally restricted by cereal export bans. Thus, it can be considered a relatively closed economy for maize. However, cross-border trade with neighboring countries still goes on even when cereal export bans are in effect. As a result, we assess poverty impacts of maize CGI under both extreme cases (small open economy and closed economy), 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:

$$\Delta\hat{I}_{ik} = \left(PY_{ik}^{OBS} - C_{ik}^{OBS}\right) - \left(PY_{ik}^{CT} - C_{ik}^{CT}\right) = P\Delta\hat{Y}_{ik} - \Delta\hat{C}_{ik} \tag{6}$$

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:

$$\Delta\hat{I}_{i} = \sum\nolimits_{k}\left(P\Delta\hat{Y}_{ik} - \Delta\hat{C}_{ik}\right) \tag{7}$$

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]

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[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.

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):

$$K = \left(\frac{\hat{\varphi}}{\varepsilon} - \frac{\hat{\theta}}{1 + \hat{\varphi}} \right) \times \text{Adoption rate} \tag{8}$$

where ε is the supply elasticity; $\hat{\varphi}$ and $\hat{\theta}$ are yield and cost ATTs estimated through equations (4) and (5). The yield and cost ATTs from MTE estimation are employed in equation (8) 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 equation (9):

$$P^{CT} = P^{OBS} (\varepsilon + \eta) / (\varepsilon + \eta - K\varepsilon) \tag{9}$$

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, $(P^{CT} - P^{OBS}) / P^{CT}$:

$$\Delta PS = P^{CT} Q^{CT} (K - Z)(1 + 0.5 Z\eta) \tag{10}$$

$$\Delta CS = P^{CT} Q^{CT} Z (1 + 0.5 Z\eta) \tag{11}$$

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.

2.3.3. 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:

$$\Delta PS = \Delta PS_{PRICE} + \Delta PS_{ADOPTION} \tag{12}$$

It is difficult to directly compute $\Delta PS_{ADOPTION}$ as it involves yield and cost changes due to adoption which vary across households. However, it is possible to compute ΔPS_{PRICE} at the market level as the price drop is unique for all market participants. Mathematically, it can be shown that:

$$\Delta PS_{PRICE} = \frac{K\varepsilon P^{OBS} Q^{CT}}{\varepsilon + \eta - K\varepsilon}\left(\frac{K\varepsilon P^{OBS}}{2P^{CT}(\varepsilon + \eta - K\varepsilon)} - 1\right) \tag{13}$$

$\Delta PS_{ADOPTION}$ is then computed as the residual between ΔPS, evaluated through equation (10), and ΔPS_{PRICE} as computed above.

ΔPS_{PRICE} is allocated to all maize sellers based on their market shares, because only sellers suffer from the price drop. 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 equation (8):

$$w_i = \frac{K_i A_i}{\sum_i K_i A_i} \tag{14}$$

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.

2.3.4. Poverty impact estimation

Two counterfactual income distributions corresponding to the open and closed economy case 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.

2.4. 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 resulting 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 gathered as recall data from the previous cropping season.

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 under circumstances where seed markets are underdeveloped or missing. 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. After accounting for sampling weights, our data suggest an adoption rate of improved maize of 39.1% by area. There is no dominant variety and hybrids are generally more popular than OPVs.

Among the 1,359 households, there are 503 adopters, 583 non-adopters, 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 than non-adopters. The survey also asks about

[2] There are several reasons for this categorization. First, the pollination process is controlled and varieties may cross with each other if plots are close. Second, OPVs are a collection of varieties with different characteristics such as drought tolerance and pest resistance. As 2010 was a good cropping year, drought tolerance advantages of OPVs do not come into play. Third, the mean per-hectare yields of hybrids and OPVs in the data differ by small amounts. See Figure 1 for the kernel density estimations of yields of the three variety types.

the intention to adopt improved maize varieties in the future. Results show that adoption is increasing over time as 71.7% of non-adopters are interested in adopting improved varieties 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. 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 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

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

including Ethiopia (see 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 non-poor. The observed poverty headcount ratios are noticeably higher among non-adopters.

2.5. Results

2.5.1. 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 (productivity 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

[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

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 were 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 resources such as seed dealer, etc. 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

estimates to the main result. Since this IV does not add much to the model, the results with the full set are reported.

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, the IVs pass a series of tests of endogeneity, under-identification, over-identification and weak identification.

A Cobb-Douglas production function is estimated via 2SLS, Probit-2SLS and GMM procedures to reveal yield ATT, or $\hat{\varphi}$. 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, the results from the different estimation procedures are numerically close. Depending on the model, $\hat{\varphi}$ is estimated to be between 47.6% - 63.3%. A flexible translog functional form is also estimated, and $\hat{\varphi}$ is estimated as 53.5% - 61.6%. This closeness builds confidence in the estimates.

Estimated yield MTEs are highest among mid-low propensity scores, as observed using both Cobb-Douglas (Figure 2a) and translog function form (Figure 2b). These results 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 the households grow maize 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 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, pesticides)[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 with respect to endogeneity, under-identification, over-identification and weak identification.

Results are reported in the lower panel of Table 4. Assuming either homogeneous or heterogeneous treatment effect, $\hat{\theta}$ 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 generally decrease as propensity scores increase (Figure 3a and 3b). Regressions of MTE on propensity scores yield a negative slope with 1%

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[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.

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 costs of additional inputs even if the yield potential is high.

2.5.2. 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.

Three matching techniques are employed: nearest neighbor matching, radius matching, and kernel matching. The yield ATT is estimated to be 43.4% - 48.9% (all with 1% significance), numerically close to the regression estimates. PSM is also applied to cost ATT estimation and a per hectare cost increase of 22.1% - 25.6% is found (with at least 5% significance).

Finally, the yield ATT $\hat{\varphi}$ is estimated using the subsample of 273 partial adopters with 772 plot-level observations. $\hat{\varphi}$ 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 non-adopting plots in equation (4):

$$\Delta y_{ikl} = \varphi + \beta_{kl}\Delta X_{ikl} + \Delta u_{ikl} \tag{15}$$

where the difference is taken between the plot k (improved) and plot l (local) for the i^{th} household; β_{kl} is the coefficient and ΔX_{ikl} is the vector of input differences. This vector of input differences cancels out observed and unobserved household-level heterogeneity and identifies the treatment effect 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 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.

Although the first-difference type procedure in equation (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 non-adopting 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 the econometric estimates.

2.5.3. 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 of both maize supply and demand are obtained from existing literature, followed by sensitivity analyses for robustness check of poverty estimates. From the large literature that suggests a wide variation of maize supply and demand elasticities in Sub-Saharan Africa (e.g. Jayne et al., 1995; Abrar et al., 2004; Omamo et al., 2007; Alene et al., 2008), 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 US dollar per kilogram.[6] With

[6] The producer price is used here as statistics on retail price are limited. The eleven-year average is used since a price peak is observed during 2007-2009 due to the global commodity price spike, and a smaller average will lead to more conservative poverty impact estimates. It may be argued that the single average FAOSTAT producer price is not the actual price received by farmers, but this price is lower than 80% of the producer prices observed in our data.

P^{OBS}, the k-shift is computed as a 37.4% cost reduction per kilogram of maize. A P^{CT} of 0.191 US 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 75,118 producer surplus gain (with ΔPS_{PRICE} being USD -32,929 and $\Delta PS_{ADOPTION}$ being USD 108,047) and a USD 37,559 consumer surplus gain are allocatable to surveyed households.[8] The data also suggests that 6.37% of the consumer surplus change goes to maize producing households according to their consumption share of their maize supply[9], and thus almost all measured welfare impacts occur through producer surplus changes. Benefits for maize-producing households average 2.4 US cents per person per day, but some households benefit by much more and some by much less, depending on the yield and cost MTEs.

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[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 sampling strategy is designed to be representative of all maize producers in Ethiopia. Sample weights are used to make inferences to the broader maize-producing population.

[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.

2.5.4. Assessing poverty impacts

The counterfactual and observed income distributions are used to measure poverty. The three poverty lines of $1, $1.25 and $1.45 per person per day are again 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 under the assumption of a small open economy, where the poverty headcount ratio fell by 0.9 - 1.3 percentage points, as compared to 0.8 - 0.9 percentage points in the closed economy. This is intuitive as the profitability of maize decreases as market price drops, and only a small portion of total consumer surplus is enjoyed by maize-producing households. 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; a 2.3 - 3.1 % decrease in poverty depth and a 3.1 - 4.0 % decrease in poverty severity are observed. Results are robust across all poverty lines.

Several parameters can affect the final poverty impact estimates, including the estimated treatment effects ($\hat{\varphi}$ and $\hat{\theta}$), elasticities (ε and η), the adoption rate and the

[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 .2987 and .0093, respectively. Thus, the percentage of the originally poor who have escaped poverty is .0093 / .2987 = .0311, or 3.1%. Similar computations are applied to poverty depth and severity.

proportion of maize supply purchased by rural households. As an analysis of sensitivity, joint variations of these parameters are allowed and differences in poverty indices are obtained. Results suggest the current poverty estimates are rather conservative.[11]

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 equally felt by different households. 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 small because as only 6.37% of the consumer surplus gain is accrued to maize-producing households). As seen in Figure 4, poor adopters are found to benefit the least. While poor farmers are further found as likely to adopt as the non-poor, and their yield and cost MTEs are similar, they are able to adopt on far smaller areas. The smallness of land holdings explains why the poor receive few benefits.

2.6. Concluding remarks

Maize research and subsequent adoption of research-produced technologies have had

[11] Details are available upon request.

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 non-adopters 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 were 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 non-adopters cannot be overemphasized. Other micro-level 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.

References

Abrar, S., Morrissey, O., Rayner, T., 2004. Crop-level supply response by agro-climatic region in Ethiopia. *J. Agr. Econ.* 55: 289–311.

Alene, A. D., Coulibaly, O., 2009. The impact of agricultural research on productivity and poverty in sub-Saharan Africa, *Food Policy* 34, 198-209.

Alene, A. D., Hassan, R. M., 2006. Erratum: The efficiency of traditional and hybrid maize production in Eastern Ethiopia: an extended efficiency decomposition approach. *J. Afr. Econ.* 15(2), i-xxvii.

Alene, A. D., Manyong, V. M., Omanya, G., Mignouna, H. D., Bokanga, M., Odhiambo, G., 2008. Smallholder market participation under transactions costs: maize supply and fertilizer demand in Kenya. *Food Policy* 33: 318-328.

Alston, J. M., Chan-Kang, C., Marra, M. C., Pardey, P. G., Wyatt, T. J., 2000. A meta-analysis of rates of return to agricultural R&D. Research Report 113, International Food Policy Research Institute, Washington D.C.

Alston, J. M., Norton, G. W., Pardey, P. G., 1995. *Science under Scarcity: Principles and Practice for Agricultural Research and Priority Setting*. Cornell University Press, Ithaca, NY.

Becerril, J., Abdulai, A., 2010. The impact of improved maize varieties on poverty in Mexico: a propensity score-matching approach. *World Dev.* 38, 1024-1035.

Beegle, K., Carletto, C., Himelein, K., 2012. Reliability of recall in agricultural data. *J. Dev. Econ.* 98: 34-41.

Chamberlin. J., Schmidt, E., 2012. Ethiopian agriculture: a dynamic geographic perspective. In P. Dorosh and S. Rashid, eds., *Food and Agriculture in Ethiopia: Progress and Policy Challenges*. University of Pennsylvania Press, Philadelphia, PA.

Chen, S., Ravallion, M., 2010. The developing world is poorer than we thought, but no less successful in the fight against poverty. *Q. J. Econ.* 125, 1577-1625.

Chernozhukov, V., Hansen, C., 2005. An IV model of quantile treatment effects. *Econometrica* 73, 245-261.

de Janvry, A., Sadoulet, E., 2002. World poverty and the role of agricultural technology: direct and indirect effects. *J. Dev. Stud.* 38, 1-26.

Dercon, S., Gilligan, D. O., Hoddinott, J., Woldehanna, T., 2009. The impact of agricultural extension and roads on poverty and consumption growth in fifteen Ethiopian villages. *Am. J. Agr. Econ.* 91, 1007-1021.

Evenson, R. E., Gollin, D., 2003. *Crop Variety Improvement and Its Effect on Productivity: The impact of international agricultural research*. CABI Publishing, Wallingford, UK.

Foster, J., Greer, J., Thorbecke, E., 1984. A class of decomposable poverty measures. *Econometrica* 52, 761–766.

Hansen, L. P., 1982. Large sample properties of generalized method of moments estimators. *Econometrica* 50, 1029–1054.

Heckman, J. J., 1979. Sample selection bias as a specification error. *Econometrica* 47, 153-161.

Heckman, J. J., Urzua, S., Vytlacil, E., 2006. Understanding instrumental variables in models with essential heterogeneity. *Rev. of Econ. Stat.* 88, 389-432.

Imbens, G. W., Angrist, J. D., 1994. Identification and estimation of local average treatment effects. *Econometrica* 62, 467-475.

Jacoby, H. G., 1993. Shadow wages and peasant family labour supply: an econometric application to the Peruvian Sierra. *Rev. Econ. Stud.* 60, 903-21.

Jayne, T., Lupi, F., Mukumbu, M., 1995. Effects of food subsidy elimination in Kenya: an analysis using revealed and stated preference data. Economics Staff Paper No. 95-23. Depart. of Agr., Food and Res. Econ., Michigan State University, East Lansing, MI.

Karanja, D. D., Renkow, M., Crawford, E. W., 2003. Welfare effects of maize technologies in marginal and high potential regions of Kenya. *Agric. Econ.* 29, 331-341.

Kassie, M., Shiferaw, B., Muricho, G., 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. *World Dev.* 39, 1784-1795.

Lin, J. Y., 1991. Education and innovation adoption in agriculture: evidence from hybrid rice in China. *Am. J. Agr. Econ.* 73, 713-723.

Mal, P., Anik, A. R., Bauer, S., Schumitz, P. M., 2012. Bt cotton adoption: a double-hurdle approach for North Indian farmers. *AgBioForum* 15: 294-302.

Manyong, V. M., Kling, J. G., Makinde, K. O., Ajala, S. O., Menkir, A., 2003. Impact of IITA germplasm improvement on maize production in West and Central Africa, in: R.E. Evenson and D. Gollin, eds., *Crop Variety Improvement and Its Effect on Productivity: The Impact of International Agricultural Research.* CAB International, Wallingford, UK.

Maredia, M. K., Byerlee, D., Pee. P., 2000. Impacts of food crop improvement research: evidence from sub-Saharan Africa, *Food Policy* 25, 531-559.

Marenya, P. P., Barrett, C. B., 2007. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in Western Kenya. *Food Policy* 32, 515-536.

Matuschke, I., Mishra, R. R., Qaim, M., 2007. Adoption and impact of hybrid wheat in India. *World Dev.* 35: 1422-1435.

McKay, A., 2000. Should the survey measure total household income? In M. Grosh and P. Glewwe, eds., *Designing Household Survey Questionnaires for Developing Countries: Lessons from Fifteen Years of Living Standard Measurement Study, Vol. 2*. The World Bank, Washington D.C.

Mendola, M., 2007. Agricultural technology adoption and poverty reduction: a propensity-score matching analysis for rural Bangladesh. *Food Policy* 32, 372-393.

Mills, B., 1997. Ex-ante agricultural research evaluation with site-specific technology generation: the case of sorghum in Kenya. *Agric. Econ.* 16, 125-138.

Minten, B., Barrett, C. B., 2008. Agricultural technology, productivity, and poverty in Madagascar. *World Dev.* 36, 797-822.

Norton, G.W., Alwang, J., forthcoming (2014). The role of impact assessment in evaluating agricultural R&D. In N. Beintema, J. Lynam and O. Badiane, eds. *The Future of Agricultural Research in Africa South of the Sahara: Synergizing Resources, Innovation, and Partnerships*, IFPRI-ASTI, Washington DC, in press.

Omamo, S. W., Diao, X., Wood, S., Chamberlin, J., You, L., Benin, S., Wood-Sichra, U., Tatwangire, A., 2006. Strategic priorities for agricultural development in Eastern and Central Africa. IFPRI Research Monograph No. 150. International Food Policy Research Institute. Washington D.C.

Renkow, M., Byerlee, D., 2010. The impacts of CGIAR research: a review of recent evidence. *Food Policy* 35, 391–402.

Rosenbaum, P. R., 2002. *Observational Studies*. 2nd ed. Springer, New York.

Rubin, D. 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *J. Educ. Psychol.* 66, 688-701.

Schneider, K., Anderson, L., 2010. Yield gap and productivity potential in Ethiopian agriculture: staple grains & pulses. EPAR Brief No. 98. Evans School Policy Analysis and Research. University of Washington, Seattle, WA.

Seyoum, E. T., Battese, G. E., Fleming, E. M., 1998. Technical efficiency and productivity of maize producers in eastern Ethiopia: a study of farmers within and outside the Sasakawa-Global 2000 project, *Agric. Econ.* 19, 341-348.

Shiferaw, B., Smale, M., Braun, H. J., Duveiller, E., Reynolds, M., Muricho, G., 2013. Crops that feed the world 10. Past successes and future challenges to the role played by wheat in global food security. *Food Security* 5, 291-317.

Smale, M., Just, R. E., Leathers, H. D., 1994. Land allocation in HYV adoption models: an investigation of alternative explanations. *Am. J. Agr. Econ.* 76, 535–546.

Strauss, J. 1986. The Theory and Comparative Statics of Agricultural Household Models: A General Approach. In I. Singh, L. Squire, and J. Strauss, eds. *Agricultural Household Models: Extensions, Applications and Policy.* Baltimore: Johns Hopkins University Press.

Suri, T., 2011. Selection and comparative advantage in technology adoption. *Econometrica* 79, 159-209.

Wooldridge, J. M., 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.

Table 2.1. Descriptive Statistics of Maize Households by Adoption Type[1]

	Adopters (n = 503)	Non-adopters (n = 583)[2]	Partial-adopters (n = 273)[2, 3]
Total cultivated area (ha)	2.02 (1.51)	1.86 (1.33)	2.37**, ††† (1.89)
Total maize area (ha)	.709 (.674)	.553*** (.545)	1.09***, ††† (1.17)
Household size	6.58 (2.46)	6.29** (2.21)	6.91*, ††† (2.40)
Total household wealth[4] (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[5]	.549 (.492)	.592 (.498)	.582 (.494)

[1] Standard deviations are in parentheses.
[2] *, **, *** indicate significance at 1%, 5% and 10% level in pairwise t-tests with adopters.
[3] †, †† and ††† indicate significance at 1%, 5% and 10% level in pairwise t-tests with non-adopters.
[4] 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.
[5] Defined as no education at all, as opposed to at least some education.

Table 2.2. Summary of Plot Characteristics and Maize Cropping Practice

	Improved[1] (n = 1214)	Local[1] (n = 1282)	Difference[2]
Plot characteristics			
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)
Maize cropping practice			
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] (ETB[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)
Input cost (ETB per ha)	2133.2 (39.7)	1638.4 (32.5)	494.8 (.000)

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

Table 2.3. Descriptive Statistics of Household Characteristics by Poverty Status[1, 2]

Poverty line ($ per person per day)	$1		$1.25		$1.45	
Poverty status	Non-poor (n=955)	Poor (n=404)	Non-poor (n=778)	Poor (n=581)	Non-poor (n=667)	Poor (n=692)
Household size	6.191	7.317***	6.057	7.153***	5.954	7.077***
Total assets (ETB)[2]	20,220	10,010***	22,076	10,635***	23,680	10,924***
Head gender (1 = M; 0 = F)	.934	.955	.936	.947	.934	.947
Head age (years)	42.80	43.63	42.70	43.52	42.83	43.27
Head marital status (1 = married; 0 = other)	.924	.955**	.923	.947*	.922	.945
Head education (years)	2.902	2.376***	2.960	2.458***	2.988	2.512***
Head illiterate (1 = yes; 0 = no)	.520	.594**	.528	.604***	.537	.607***
Poverty headcounts among non-adopters	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%	

[1] ***, **, * denote that the difference between non-poor and poor is significant at 1%, 5% and 10% level via t-test, respectively.

[2] Household income per person per day is used as the welfare measure. Official daily average exchange rate in 2010 is used.

[3] Computed as the sum of the self-reported values of all household assets.

Table 2.4. Estimation of Yield and Cost ATTs[1]

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

[1] 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 available upon request.

Table 2.5. Poverty Impacts of Improved Maize Varieties

Poverty line (USD per person per day)	FGT poverty index	Observed	Small open economy	Poverty impact[1]	Closed economy	Poverty impact[1]
	Headcount	.2894	.2987	.0093	.2973	.0079
1	Depth	.0963	.0994	.0031	.0991	.0028
	Severity	.0435	.0453	.0018	.0449	.0014
	Headcount	.4162	.4291	.0129	.4255	.0093
1.25	Depth	.1496	.1534	.0038	.1537	.0041
	Severity	.0724	.0748	.0024	.0749	.0025
	Headcount	.4957	.5057	.0100	.5043	.0086
1.45	Depth	.1947	.1996	.0049	.1992	.0045
	Severity	.0983	.1021	.0038	.1020	.0037

[1] All poverty impacts are reported as percentage point reductions compared to the counterfactual.

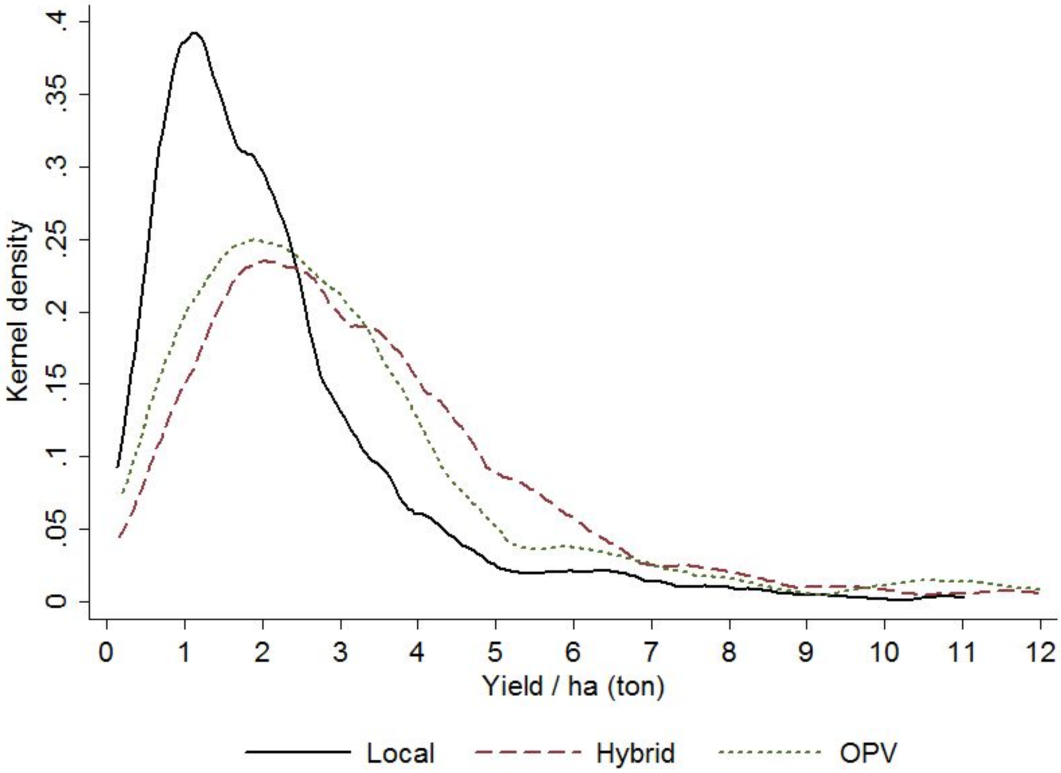
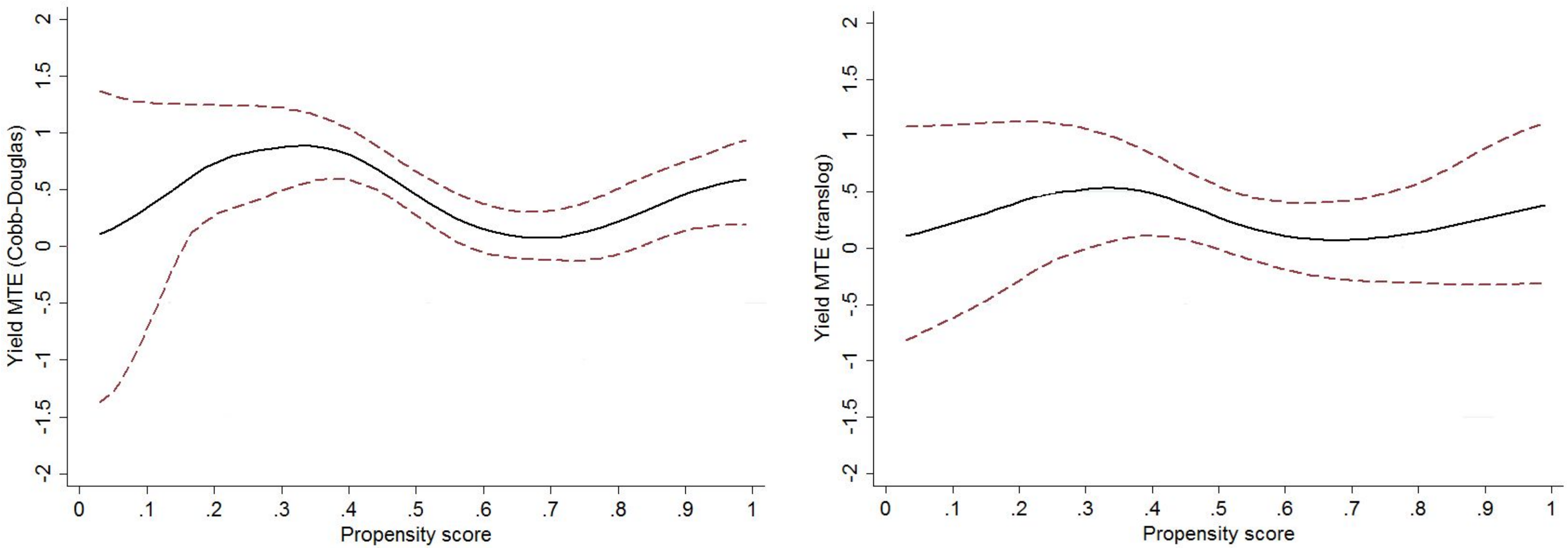


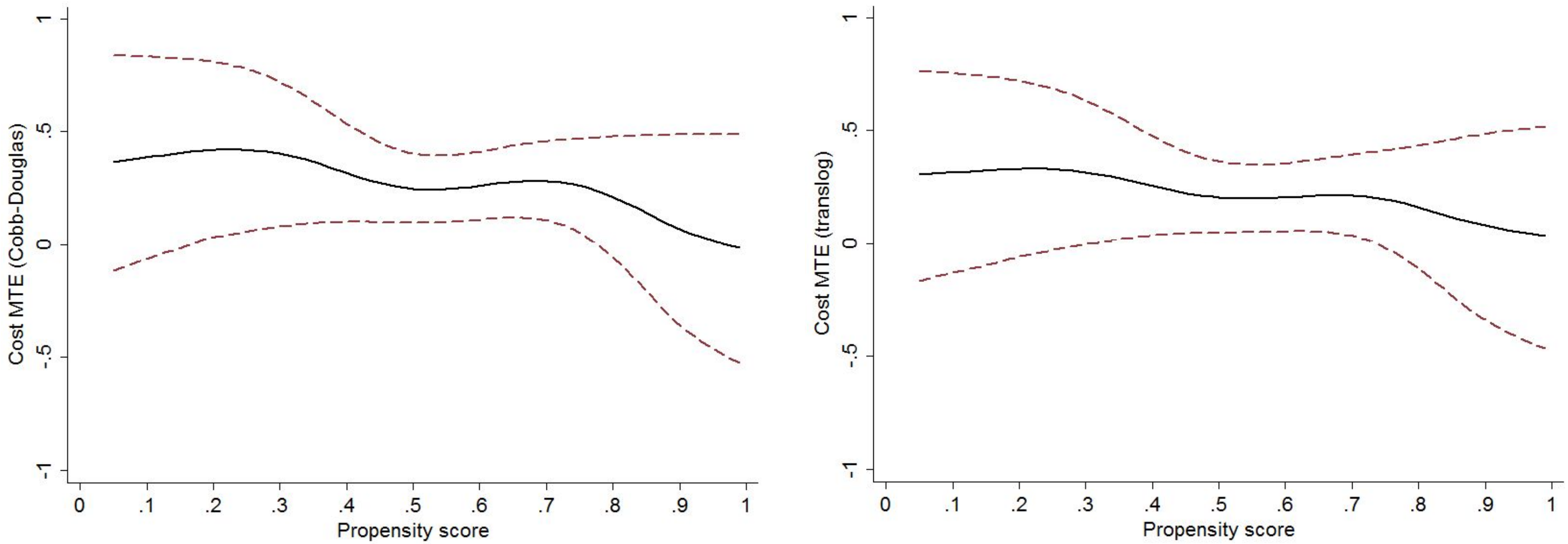
Fig. 2.1. Kernel Density Estimation of Yields of Different Maize Varieties



(a) (b)

Fig. 2.2. Yield Marginal Treatment Effect Estimation[1]

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



(a) (b)

Fig. 2.3. Cost Marginal Treatment Effect Estimation[1]

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

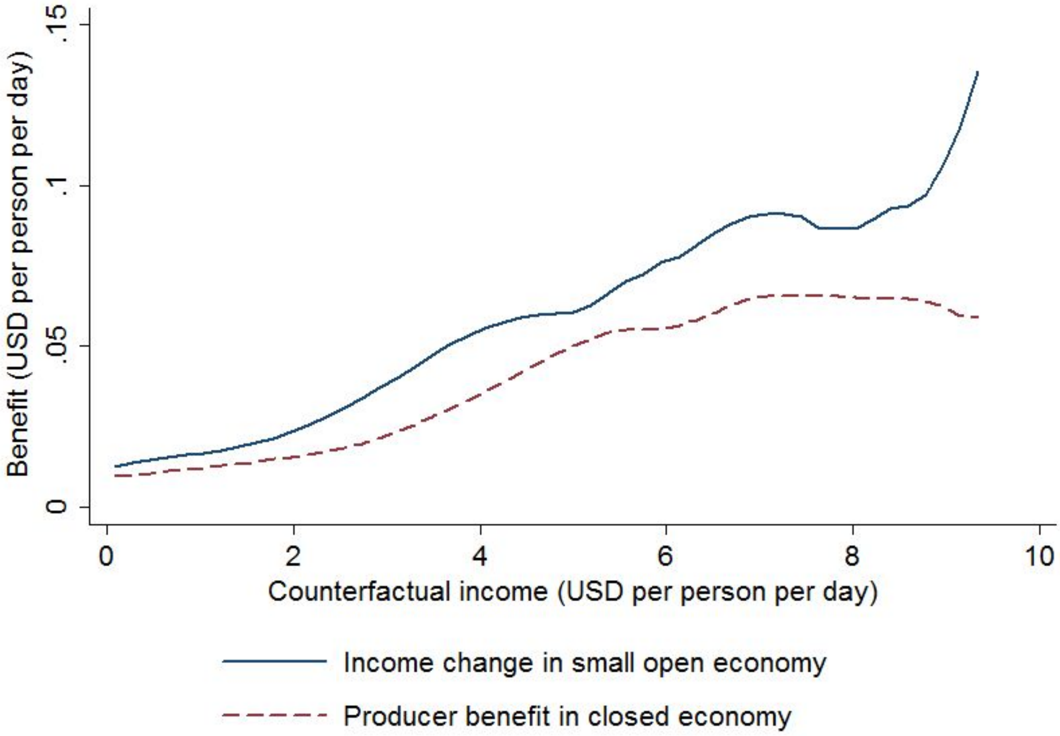


Fig. 2.4. Benefits Due to Adoption Across Counterfactual Income Levels[1]

[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.

Chapter 3

Essay2: Impacts of Improved Maize Varieties on Child Nutrition in Ethiopia

3.1. Introduction

Crop genetic improvement (CGI) is used to enhance the productivity or quality of food crops and improve the wellbeing of rural households and society in general. In developing countries, multidimensional welfare impacts are expected through adoption of improved varieties, including poverty reduction, food security enhancement, and better nutrition outcomes. In Sub-Saharan Africa (SSA), investments on CGI research have been substantial, with extensive literature documenting the spread of improved varieties and its impact on productivity (Maredia et al., 2000; Evenson and Gollin, 2003; Alene and Coulibaly, 2009). Although the welfare impacts of CGI are receiving increasing attention (e.g. Karanja et al., 2003; Moyo et al., 2007; Kassie et al., 2011; Zeng et al., 2013), most studies focus on income generation and poverty reduction, with nutrition improvement rarely explored. This gap needs to be filled as malnutrition reduction is a long-term goal for major international development efforts (e.g. UNICEF, 2013), and policy makers need such information to optimally allocate resources to achieve this goal.

Maize is a widely grown food and cash crop 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 1960 to 2009, the dietary calorie and protein contributions of maize in Ethiopia have doubled to around 20% and 16%, respectively (Shiferaw et al., 2013). As a major staple crop, maize receives substantial funding from the national and international agricultural research system. In the last four decades, more than 40 improved maize varieties (IMVs), including hybrids and improved open-pollinated varieties (OPVs), have been developed and released in Ethiopia through the Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the International Maize and Wheat Improvement Center (CIMMYT). These IMVs are intended to increase productivity or stabilize it in risky agroecological environments. Although most of these IMVs have been widely adopted for years, their impacts on child nutrition remain largely unknown.

This paper helps fill this gap by exploring the impacts of IMV adoption on child nutrition using a recent household survey that collects data among children up to 60 months old. Multiple channels may form the link between IMV adoption and nutritional outcomes. For example, children in adopting households may increase calorie intake by consuming more own-produced maize due to higher yields. Adopting households may have access to more foods with increased disposable income from sales of additional maize production. Income-related impacts can also occur through increased consumption of non-food items, and investments in nutrition technology such as improved water, sanitation and cooking practices. On the other hand, consumption of other own-produced foods may be affected if IMV adoption alters the acreage allocation between maize and other food crops. Such impacts can be negative as maize area expansion would shrink the total acreage available for other food crops, and this tradeoff can be nontrivial for smallholders, who comprise the majority of Ethiopian farmers. These possible pathways need to be explored to fully understand any causal linkages between IMV adoption and child nutrition outcomes.

An agricultural household model is used to demonstrate the conceptual relationship between IMV adoption and child nutrition outcomes. The empirical specification is then derived from the theoretical model and estimated using instrumental variable (IV) techniques that account for the endogeneity of acreage allocation decisions. IMV adoption has significant impacts on child nutrition outcomes. One kert (0.25 hectare) of IMVs improves child height-for-age and weight-for-age z-scores by 0.26 and 0.18 standard deviations, respectively. Results from quantile IV regressions further suggest that such impacts are largest among children with the worst nutritional outcomes, or the most severely malnourished. The pathways by which IMV adoption affects nutrition are illuminated through decompositions of estimates from a system of equations. Increased own-produced maize consumption appears as the major pathway by which IMV adoption affects child nutrition.

3.2. Literature

At the farm household level, welfare impacts of agricultural technologies primarily occur through adoption, a decision made by the farmer. Welfare changes are directly felt by adopters through higher crop yields and reductions in unit costs of production, which in turn increase own consumption and disposable income. Economic impacts may also indirectly affect non-adopting producers and consumers, for example, through market price changes caused by the technology-induced supply increase (Zeng et al., 2013). A large literature links CGI to positive aggregate economic impacts in SSA (Maredia et al., 2000; Alene and Coulibaly, 2009). Distributional impacts have also received increasing attention, with most research attention on household-level changes in income and poverty (Karanja et al., 2003;

Moyo et al., 2007; Kassie et al., 2011).

Most CGI evaluations focus on the economic impacts, while empirical work on nutrition benefits from varietal improvements is limited. The only exception is the public health literature investigating the impacts of crop biofortification on human nutrition improvement, including studies on orange-fleshed sweet potato (e.g. Low et al., 2007; Hotz et al., 2012) and quality protein maize (e.g. Akuamoa-Boateng, 2002; Gunaratna et al., 2010). These studies consistently suggest nutrition improvements from crop biofortification. However, as most improved crop varieties are not biofortified, the general impacts of CGI on human nutrition remain largely unknown. Also, most assessments of biofortification employ randomized controlled trials which facilitate identification of causal effects. Randomized controlled trials are mainly suitable for impact assessment of new technologies, but are not appropriate in uncovering the impacts of existing technologies which have already been widely diffused.

Child nutrition is an important focal area for welfare improvement and long-term development. Improvements in child nutrition can reduce mortality (Behrman et al., 2004) and increase adult heights (Alderman et al., 2006), which directly increase long-term agricultural productivity. Child nutrition also affects economic and social development through its impact on education. Specifically, child malnutrition has been found to cause delayed school enrollment (Glewwe and Jacoby, 1995), poor school performance (Alderman et al., 2006), far fewer years of schooling and less learning per year of schooling (Glewwe and Miguel, 2007). The impairment of cognitive function and loss of schooling can result in the intergenerational transmittal of poverty (Behrman et al., 2004). The production of child nutrition is a complex process. Economic evidence from developing countries suggest several key determinants of nutrition outcomes, including household income (Skoufias, 1998) and food security (Reis, 2012), parental education (Thomas et al., 1991), availability of local infrastructure such as modern sewerage, piped water and electricity (Thomas and Strauss, 1992), and sibling rivalry (Behrman, 1988; Garg and Morduch, 1998). There is also evidence of a gender gap between nutrition outcomes of boys and girls in SSA (Garg and Morduch, 1998), where girls have poorer nutrition status than boys. Most studies employ observational data to establish linkages between causal factors and child nutrition outcomes through the estimation of reduced form regressions derived from household models. Although statistical evidence of overall impacts is generally found in this literature, only a few estimate structural models showing the mechanisms that household decisions affect nutrition outcomes (Glewwe, 1999). As a result, causal pathways have not been widely explored.

3.3. Analytical framework

The theoretical relationship between IMV adoption and child nutrition is established in an agricultural household model. Assume farm household i maximizes utility of the following form:

(1) $$U_i(M_i, F_i, R_i, C_i, \{N_{ij}\})$$

where M_i, F_i, R_i and C_i are consumption of own-produced maize, other own-produced foods, purchased foods, and purchased non-food items, respectively. N_{ij} is the nutrition status of child j in household i, and the nutrition status of all children enters the household utility (which jointly appear in the bracket). Further, for each child j, N_{ij} is a function of the individual-level consumption of that child, household characteristics, H_i, and child characteristics, G_{ij}:

(2) $$N_{ij} = N_{ij}(M_{ij}, F_{ij}, R_{ij}, C_{ij}, H_i, G_{ij})$$

Consumption of child *j* is a proportion of overall consumption of household *i*, where the proportion θ_{ij}, the resource allocation decision within the household, can be a function of both household and child characteristics. If ϕ is used to denote consumption type of either child *j* (with subscript *ij*) or household *i* (with subscript *i*), the household allocation decision can be represented as:

(3) $$\phi_{ij} = \theta_{ij}(H_i, G_{ij}) \cdot \phi_i\,, \quad \phi = M, F, R, C$$

The household is assumed to produce maize and other food crops. Total maize production is affected by variable input use, total maize acreage and acreage planted with IMVs. A single production function is assumed for all other food crops where the yield is only affected by application of variable inputs and total acreage allocated to them. The production functions can be written as:

(4) $$Q_i^M = Q_i^M(X_i^M, A_i^M, A_i^{IM})$$

(5) $$Q_i^F = Q_i^F(X_i^F, A_i - A_i^M)$$

where X_i^M and X_i^F are vectors of inputs applied to maize and other food crops that household *i* grows, respectively; A_i^M is total maize area; A_i^{IM} is area of IMVs and A_i is the total land holding of household *i*. Using I_i to denote off-farm income (e.g. income from off-farm employment and transfers), the full cash income constraint household *i* faces is shown in equation (6), where p_t ($t = R, C, M, F, X$) denotes price vectors for various consumption goods and inputs, all assumed exogenous in the agrarian economy that mainly consists of smallholders.

(6) $\quad p_R R_i + p_C C_i = [p_M (Q_i^M - M_i) - p_X X_i^M] + [p_F (Q_i^F - F_i) - p_X X_i^F] + I_i$

Equations (1) - (6) show the utility maximization problem faced by the household. Among all methodological issues related to empirical application of the model, separability is perhaps the most important one that deserves explicit discussion. If perfectly competitive markets exist for all commodities, the household's production and consumption decisions may be considered as separable (Strauss, 1986). However, such assumptions may fail to meet the reality in developing countries where certain markets (e.g. product, labor, and land) may be partially absent and thus incomplete. For example, even if all markets exist, households may be able to sell a commodity but not buy it (e.g. own crop production), and some households may consume all their production, a corner solution. In this case, shadow price of that commodity needs to be considered, which renders the household model nonseparable (Strauss, 1986). As discussed in detail below, this is the case observed for the maize market in our data. The household's problem is therefore addressed as nonseparable and production and consumption decisions are considered to be simultaneously made, and they may be jointly affected by factors such as the preferences of the household. The consumption decisions that household *i* makes is written as:

(7) $\quad \delta_i = \delta_i\left(A_i, A_i^M, A_i^{IM}, H_i, G_{ij}, I_i, P, p_X\right), \quad \delta = M, F, R, C$

where $P = (p_M, p_F, p_R, p_C)$, the price vectors of consumption items. The shadow prices of maize (p_M) and other own-produced foods (p_F) are considered endogenous, while prices of purchased foods (p_R), non-food items (p_C) and inputs (p_X) are considered exogenous.

Given equation (7) together with equation (3), the child nutrition outcome, originally shown in equation (2), now can be expressed as:

(8) $$N_{ij} = N_{ij}(A_i, A_i^M, A_i^{IM}, H_i, G_{ij}, I_i, P, p_X)$$

Equation (8) reveals the theoretical linkage between IMV adoption and child nutrition. Following most literature (e.g. Thomas et al., 1991; Currie and Cole, 1993; Thomas et al., 1996; Case et al., 2002; Berger et al. 2005), we specify a linear function form for equation (8), with an error term ε_{ij}^N :

(9) $$N_{ij} = \alpha_0 + \alpha_1 A_i + \alpha_2 A_i^M + \alpha_3 A_i^{IM} + \alpha_4 H_i + \alpha_5 G_{ij} + \alpha_6 I_i + \alpha_7 P + +\alpha_8 p_X + \varepsilon_{ij}^N$$

Maize acreage decisions, including both A_i^{IM} and A_i^M , are likely to be endogenously determined by the farmer. Unobserved factors such as adult health and household preferences are likely to affect both the nutrition outcome and acreage allocation decisions. For example, the health conditions of adults may affect both the child nutrition outcome, through unobserved genetic linkages, and maize acreage decisions, through on-farm labor supply. The child nutrition outcome can also be affected by tastes and preferences of adult members in the household, which again possibly affect IMV choices. Ignoring the choice nature of maize acreage decisions will lead to biased and inconsistent estimates of all parameters.

Assume these decisions are determined by total land holding, A_i, household characteristics, H_i, (exogenous) input prices, p_X , and a set of excluded instruments, Z_i, that affect acreage decisions and only affect child nutrition outcomes only through these decisions (discussed in detail below). The output prices, however, are excluded as they are mainly realized after the cropping season and the expectations are not captured in our cross-sectional survey, and would not logically affect the acreage decisions made at the beginning of that season. Again, specify these relationships linear forms with error terms ε_{ij}^t, respectively:

(10) $$A_i^t = \beta_0^t + \beta_1^t A_i + \beta_2^t H_i + \beta_3^t p_X + \beta_4^t Z_i + \varepsilon_i^t, \quad t = IM, M$$

Equations (9) - (10) form a simultaneous equation model that accounts for the endogeneity of maize acreage decisions. Estimation of the system leads to measurement of the overall impact of IMV adoption on child nutrition outcomes, which is captured by the coefficient α_3 in equation (9).

To fully understand the impact of IMV adoption on child nutrition outcomes, potential impact pathways need to be investigated. With the linkages between household-level and individual-level consumptions defined in equation (3), the child nutrition outcome (equation 2) can be written as:

(11) $$N_{ij} = N_{ij}(M_i, F_i, R_i, C_i, H_i, G_{ij})$$

Equation (11) replaces child *j*'s individual-level consumption of own-produced maize, other own-produced foods, purchased foods and non-food items, as seen in equation (2), with respective household-level consumption decisions as determinants of child nutrition outcome. As individual-level consumption for the child are rarely observed in household surveys, equation (11) employs observed household-level consumption while controlling for household and child characteristics. Based on equations (7), (10) and (11), a system of equations is constructed to differentiate the possible channels described above. Linear forms are again assumed following the mainstream literature:

(12.1) $$A_i^{IM} = \beta_0^{IM} + \beta_1^{IM} A_i + \beta_2^{IM} H_i + \beta_3^{IM} p_X + \beta_4^{IM} Z_i + u_i^{IM}$$

(12.2) $$A_i^{M} = \beta_0^{M} + \beta_1^{M} A_i + \beta_2^{M} H_i + \beta_3^{IM} p_X + \beta_4^{M} Z_i + u_i^{M}$$

(12.3) $$M_i = \gamma_0^M + \gamma_1^M A_i^{IM} + \gamma_2^M A_i^M + \gamma_3^M A_i + \gamma_4^M H_i + \gamma_5^M G_{ij} + \gamma_6^M I_i + \gamma_7^M P + \gamma_8^M p_X + u_{ij}^M$$

(12.4) $$F_i = \gamma_0^F + \gamma_1^F A_i^{IM} + \gamma_2^F A_i^M + \gamma_3^F A_i + \gamma_4^F H_i + \gamma_5^F G_{ij} + \gamma_6^F I_i + \gamma_7^F P + \gamma_8^F p_X + u_{ij}^F$$

(12.5) $$R_i = \gamma_0^R + \gamma_1^R A_i^{IM} + \gamma_2^R A_i^M + \gamma_3^R A_i + \gamma_4^R H_i + \gamma_5^R G_{ij} + \gamma_6^R I_i + \gamma_7^R P + \gamma_8^R p_X + u_{ij}^R$$

(12.6) $$C_i = \gamma_0^C + \gamma_1^C A_i^{IM} + \gamma_2^C A_i^M + \gamma_3^C A_i + \gamma_4^C H_i + \gamma_5^C G_{ij} + \gamma_6^C I_i + \gamma_7^C P + \gamma_8^C p_X + u_{ij}^C$$

(12.7) $$N_{ij} = \gamma_0^N + \gamma_1^N M_i + \gamma_2^N F_i + \gamma_3^N R_i + \gamma_4^N C_i + \gamma_5^N H_i + \gamma_6^N G_{ij} + u_{ij}^N$$

Equations (12.1) and (12.2) are maize land allocation decisions as in equation (10). Equations (12.3) - (12.6) are household consumption of own-produced maize, other own-produced foods, purchased foods and non-food items, all of which are linearized from equation (7). Finally, equation (12.7) is the linearization of the structural child nutrition production function derived in equation (11). Each equation has its root in previous analysis, and the system appears to be block recursive, but it is actually nonrecursive as the errors are likely to be correlated among equations. This makes sense as unobserved factors that affect IMV adoption may also affect consumption decisions and child nutrition outcome. For example, farmer *i*'s unobserved attitudes and preferences regarding food consumption may affect his/her adoption decisions, consumption decisions as well as the nutrition outcomes his/her children. Also, unknown genetic factors may affect the physical needs for foods among household members and thus affect both household food consumption and child nutrition status. Besides, the health conditions of adult family members, which are again rarely observed, can simultaneously affect the household's IMV adoption and consumption decisions. In this sense, equation by equation estimation, as usually employed for recursive systems, would be incapable to identify the system (12.1) - (12.7) above. Thus, it is necessary to estimate these equations as a nonrecursive system for correct identification of all equations and obtain unbiased and consistent coefficient estimates.

Once estimates of system (12.1) - (12.7) are obtained, a decomposition procedure similar to Glewwe (1999) can be applied to reveal the relative importance of each of these possible pathways, where ν_{ij} denotes the unexplained part of the overall impact:

$$(13) \qquad \frac{\partial N_{ij}}{\partial A_i^{IM}} = \frac{\partial N_{ij}}{\partial M_i} \cdot \frac{\partial M_i}{\partial A_i^{IM}} + \frac{\partial N_{ij}}{\partial F_i} \cdot \frac{\partial F_i}{\partial A_i^{IM}} + \frac{\partial N_{ij}}{\partial R_i} \cdot \frac{\partial R_i}{\partial A_i^{IM}} + \frac{\partial N_{ij}}{\partial C_i} \cdot \frac{\partial C_i}{\partial A_i^{IM}} + \nu_{ij}$$

Equation (13) expresses the overall impact of IMV adoption on child nutrition outcome as a sum of effects that occur through different pathways. Each pathway is considered as the product of the effect of IMV adoption on household consumption and the effect of that consumption on the child nutrition outcome. The first term of equation (13) captures direct effects through increases in own-produced maize consumption, while the third and the fourth terms reflect indirect effects through increases in consumption of purchased items with higher income. Effects through these three pathways are expected to be positive. The second term, apparently less intuitive, aims to capture any substitution effects between own-produced maize and other foods within household *i*, which can be either negative, if IMV adoption leads to expanding maize acreage and shrinking acreage available of other foods, or negligible if such acreage tradeoff is not important. Based on the coefficient estimates of system (12), equation (13) can be finally written as:

$$(14) \qquad \frac{\partial N_{ij}}{\partial A_i^{IM}} = \gamma_1^N \gamma_1^M + \gamma_2^N \gamma_1^F + \gamma_3^N \gamma_1^R + \gamma_4^N \gamma_1^C + \nu_{ij}$$

3.4. Data description

A comprehensive household survey conducted during 2009-2010 in rural Ethiopia is employed. Four regions are included in the survey: Tigray, Amhara, Oromia, and Southern Nations, Nationalities, and People's Region (SNNPR). These regions together account for more than 93% of nationwide maize production (Schneider and Anderson, 2010). The survey uses a stratified random sampling strategy that intentionally covers areas with varying maize production potential, and is nationally representative. 791 farm households from 30 woredas (districts) across these regions are included in the analysis. Basic household characteristics are recorded, and detailed cropping practices of the last cropping year, such as plot areas, amounts of inputs used and outputs produced are recalled by the farmer. Prices of inputs and outputs are reported. Household consumption of different types of own-produced foods during the last year are also based on recall. In addition to these variables, itemized market expenditures and off-farm income are collected. Table 1 provides descriptive statistics of household characteristics.

Maize varieties can be grouped into three categories: hybrids, improved open-pollinated varieties (OPVs), and local open-pollinated varieties, the first two types being categorized as IMVs. Hybrids have the highest yield, but require 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 IMVs farmers grow, inbred lines are crossed through open pollination and few plants are genetically pure. For this reason, and the empirical observation that yields of hybrids and OPVs are very close, varieties are only differentiated as being either improved (IMVs) or local, with no further differentiation between hybrids and OPVs. As suggested by local breeding scientists, any hybrids ever recycled or OPVs recycled for more than three seasons are categorized as local due to the loss of yield potential after seed recycling.

Accounting for sampling weights, the estimated IMV adoption rate is 39.1% by area.

Nutrition outcomes are based on anthropometric measurement of children up to 60 months old. A total of 1,216 children from these 791 households, including 613 boys and 603 girls, are present in the data. Heights and weights are recorded via tape measure and scale. The original measures are converted into height-for-age z-scores (HAZ) and weight-for-age z-scores (WAZ) using WHO growth standards. Figure 1 presents the distributions of both measures. The HAZ and WAZ of most children in rural Ethiopia are below WHO growth standards (graphed as standard normal). The median HAZ and WAZ are -1.48 and -.68 standard deviations below the respective standards.

3.5. Empirical results

The empirical analyses are organized as follows. To investigate the overall (mean) impacts of maize varietal adoption on child nutrition outcomes, the simultaneous equation model as described in equations (9) and (10) is first estimated using IV procedures. The model is further estimated using quantile IV techniques to uncover possible variation of the impacts among children of different nutrition status. Finally, the system of equations (12.1) - (12.7) is estimated to explore possible pathways that IMV adoption affects child nutrition outcomes, including consumption changes in own-produced maize, other own-produced foods, purchased foods and non-food items. The decomposition procedure in equations (13) and (14) is used to reveal relative importance of each of these different pathways.

Estimation of the simultaneous equation model in equations (9) and (10) is facilitated by IV techniques that correct for the endogeneity of maize acreage decisions, including IMV acreage and the total maize acreage. Three IVs are employed: the number of years the farmer has been aware of the IMV,[1] an elicited binary indicator of the existence of temporary disruption(s) in maize seed supply during the sowing month of last cropping season, and the distance to the nearest maize seed dealer from the farmer's home. The distance to the nearest seed dealer is measured in walking minutes reported by the farmer, and within-village variations are observed in the data.

All IVs are assumed to not directly affect child nutrition outcomes other than through their effects on IMV adoption. Their validity requires further discussion. It may be argued that the distance to the nearest seed dealer may possibly be correlated to distances to health facilities and main markets, both of which may also affect child nutrition status in perceivable and unperceivable ways. Such correlation with either distance might invalidate the appropriateness of the IV. However, farmers usually purchase seeds from agricultural extension offices which exist in almost every village in rural Ethiopia, but health facilities as well as main markets are usually shared by several villages, so this concern should be minimized. To further help establish the appropriateness of the distance to the nearest seed dealer as an IV, its correlations with distances to the nearest health center and to the main market, both of which may affect child nutrition outcomes are examined. Neither correlation is found significant,[2] and thus it should satisfy the exclusion restriction. Concern may also exist regarding the measurement accuracy of the elicited seed supply disruption indicator.

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[1] Farmers are asked in which year he / she first knew of the IMV, and the number of years are computed as the difference between the reported year and 2010.

[2] Pearson correlation coefficient of the IV with distance to the nearest health center is 0.021 ($p = 0.462$), and with distance to the main market is 0.045 ($p = 0.119$).

However, confidence in the validity of this measure is strengthened because the survey shows that reported seed supply disruptions cluster in certain villages. While intuitively plausible, these IVs also go through a series of rigorous tests of their suitability during empirical estimation.

Two models are estimated where N_{ij} is measured using HAZ and WAZ.[3] In each model, explanatory variables follow the empirical specification in equation (9). Child characteristics include gender, age (in months), age-square and the number of siblings up to 60 months old. Household features include total household wealth (computed as the total present value of all itemized assets), total land area, total off-farm income, the gender, age, education and marital status of household head, and three binary indicators that measure if the household has a private toilet and access to piped drinking water, and if their history of IMV adoption is at least as long as the age of each specific child up to 60 months old.[4] The first two dummies are included to capture sanitation conditions, while the third is included to detect any cumulative effects of IMV adoption on child nutrition outcomes over time. Also included are prices of maize and other staple foods (teff, wheat, barley), input prices (of maize seeds and fertilizer), and the price of soap as a proxy for non-food items that may also affect child nutrition outcomes. Finally, regional dummy variables are incorporated to capture unobserved heterogeneity across regions.

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[3] The height and weight models can also be estimated as a system using IV techniques. However, it is not necessary as no cross-equation constraints on parameters are imposed. There is also no efficiency gain as all the regressors are the same for each equation where the same IVs are applied.

[4] Farmers are asked for how many years they have planted IMVs. Child age is rounded to years and compared with the adopting years. If the adopting history is at least as long as the child age, this variable takes a value of 1 (or 0 if not). Notice that adopting history is child-specific.

In our data, a small portion of households (18 out of 791) have consumed all own-produced for at least staple food (maize, teff, wheat, barley). For these households, we expect the shadow prices to be higher than market prices (Strauss, 1986), and thus use the maximum market prices observed among other households as proxies (Mekonnen, 1999). For other households, the market prices are the appropriate opportunity costs as they sell some of their produced staples (Singh et al., 1986).

In addition to the two maize area allocation decisions, the adoption history dummy may also be endogenous, as farmers who are more willing to learn about new technologies may adopt earlier. But using Wooldridge's (1995) robust score test, where the same IVs discussed above are employed and the two maize acreage decisions are treated as endogenous, the null hypothesis of exogeneity cannot be rejected ($p = 0.277$). Thus, only the two maize acreage decisions are instrumented.

In both HAZ and WAZ models, estimation is implemented using generalized method of moments (GMM). Although simple 2SLS provides consistent estimates, GMM is more flexible in that it allows for arbitrary heteroskedasticity. Simple 2SLS, 2SLS with clustered standard errors (clustered at either woreda or household levels) and 2SLS with robust standard errors have been performed. Although the point estimates of interest appear to be very close to those obtained by GMM, error heteroskedasticity has been detected in these cases according to adjusted Breusch-Pagan tests. Thus, only the IV-GMM estimation results are presented (Table 2). As shown in the lower panel of Table 2, the three IVs passed a series of tests with respect to under-identification, over identification and weak identification in each model.

IMV adoption has significant impacts on both HAZ and WAZ. Specifically, an increase in one kert[5] of IMV area leads to a HAZ increase of 0.26 and a WAZ increase of 0.18; since these are z-scores, the impacts can be interpreted as standard deviations. Such impacts are substantial as compared to the impacts of income (Skoufias, 1998) and parental education (e.g. Thomas et al., 1991; Glewwe, 1999). As coefficients on total maize area and total land holding are insignificant, these results imply that better child nutrition outcomes are attained by switching from local maize varieties to IMVs. Such findings are of direct policy relevance because most child nutrition determinants, such as the household socioeconomic conditions, are difficult to improve in the short run, while IMV adoption can be promoted through a number of policies.

Age affects child nutrition outcomes in a nonlinear manner: both HAZ and WAZ deteriorate as the child ages but at a decreasing rate (as reflected in negative coefficients of age and positive coefficients of age square, both significant at 1% level), a common finding in previous literature (e.g. Glewwe, 1999). Wealthier households and those with better-educated heads experience better child nutrition outcomes. The magnitude of the wealth impacts are small, while a one-year increase of household head's education leads to a HAZ increase by 0.07 and a WAZ increase by 0.04, respectively. The number of siblings below 60 months old negatively affects both HAZ and WAZ of the child: an additional sibling lowers HAZ and WAZ by 0.13 and 0.08, respectively. This result is consistent with previous findings of sibling competition for resources (Behrman, 1988; Garg and Morduch, 1998). Children of male-headed households are generally taller than those of female-headed

[5] 1 kert equals 0.25 hectare.

households, but gender of the household head has no significant impact on weights. Access to piped drinking water is associated with a marginally significant increase in WAZ, but no significant impact on HAZ. Finally, coefficients of the adoption history dummy appear to be significant in both models, confirming the cumulative nutrition enhancing impacts of IMV adoption over time.

The above IV procedure confirms the hypothesized impacts of IMV adoption on child nutrition outcomes, but possible differences in impacts among children with different nutrition outcomes cannot be uncovered by these mean estimates. To explore heterogeneity among outcomes, the models are estimated using quantile IV regressions. Amemiya's (1982) two-stage least absolute deviation (2SLAD) estimator is employed, which has desirable features such as strong consistency and asymptotic normality. In the 2SLAD procedure, the predicted value of A_i^{IM} and A_i^{M} are obtained in the first stage by least absolute deviation (LAD) estimation of equation (10), and then are used as regressors in the second stage LAD estimation of equation (9). The latter estimates are evaluated at each percentile of HAZ and WAZ, respectively. Standard errors are obtained by bootstrapping with 1,000 replications

Figure 2 presents the quantile IV regression results. For both nutrition indicators, the impacts of adoption on child nutrition are largest in the lower quantiles. For HAZ, the impacts in the first quintile (averaged 0.56 standard deviation) are about twice as large as the overall impact (0.26 standard deviation, as estimated previously). For WAZ, higher and significant impacts are observed in the first two quintiles (averaged 0.35 as compared to the overall impact of 0.19). The impacts are much smaller and insignificant in other quantiles of both indicators. These patterns suggest that the nutrition impacts of IMV adoption vary among children. The most noticeable nutrition improvements occur to children with poorest nutrition outcomes (those in the lowest quantiles), or the most malnourished. This is of policy significance as the reduction of child malnutrition has always been a key focus of major international development efforts (e.g. UNICEF, 2013), and IMV adoption, which is usually promoted as a means of increasing productivity, also has substantial nutrition impacts on the group in greatest need.

To uncover possible relationships between the adoption probability and child malnutrition outcomes, a probit specification of adoption with the same explanatory variables as those of equation (10) is fitted, where households who adopt IMVs on all maize plots are categorized as adopters while those who adopt no IMVs are non-adopters.[6] The adoption probability is predicted for each household. HAZ and WAZ are then regressed against adoption propensity via local polynomial regressions. Figure 3 presents the results. For both HAZ and WAZ, farmers who are least likely to adopt have children with the worst nutrition outcomes. These farmers, however, would see their children experiencing the largest nutrition improvements through IMV adoption. Thus, efforts to promote IMV adoption can be effective means of child malnutrition reduction among the worse-off population.

To further investigate associations between IMV adoption and child nutrition outcomes, the system of equations (12.1) - (12.7) is estimated. Though consumption of own-produced maize is directly reported in kilograms, each household consumes numerous types of other own-produced foods which cannot be directly aggregated. Thus, the monetary values of other own-produced foods computed using market prices (and relative shadow prices for those few

[6] 234 children from partial adopters (those households who grow both IMVs and local varieties) are excluded for simplicity.

households who consume all their production of any type of them) are employed as the dependent variable of equation (12.4). For the same reason, total expenditures on purchased foods[7] and non-food items are employed as dependent variables for equations (12.5) and (12.6), which makes sense as those indirect effects of IMV adoption occur mainly through increases in disposable income due to higher yields and increased sales of maize, and expenditures on purchased foods and non-food items serve as a natural measure of possible effects of IMV adoption on the consumption of these goods. To facilitate direct comparison between consumption types, we employ the total value of own-produced maize as the dependent variable of equation (12.3), where market prices are used for maize sellers and shadow prices are used for those who consume all produced maize.

The system of equations is estimated using a GMM 3SLS procedure. The traditional 3SLS estimator is consistent and asymptotically efficient assuming homoscedasticity among error terms, but GMM 3SLS is more desirable as it further allows for arbitrary heteroskedasticity among error terms by employing the efficient weighting matrix in the estimation procedure (Wooldridge, 2002). GMM 3SLS is also less restrictive than the full information maximum likelihood (FIML), which is widely employed in the estimation of system of equations, in that it relaxes the assumption of joint normality of the error terms. Thus, GMM 3SLS as a better procedure that requires fewer assumptions is implemented in empirical estimation.

Table 3 presents the GMM 3SLS estimates of key parameters of interest.[8] In both HAZ

[7] Household's total food expenditure includes the amount paid for maize purchase on the market, but does not include the values of own-produced maize and other foods.

[8] Full estimation results are available upon request as the system of equations is huge, and most coefficient estimates are not

and WAZ models, the consumption of own-produced maize, and total expenditures on purchased foods and non-food items are significantly affected by the IMV adoption, while such impact on the consumption of other own-produced foods is insignificant. Maize consumption increases following IMV adoption. A one kert increase in IMV acreage raises household own-produced maize consumption by 294 Ethiopian birrs (98.29 kilograms on average, 20.59 US dollars in 2010), as captured by γ_1^M in Table 3, after controlling for household size and other characteristics. Adoption is also associated with increases in household expenditures on non-food items (γ_1^C). But a one kert increase in IMV acreage reduces total household food expenditure by 228 Ethiopian birrs annually (γ_1^R , 15.86 US dollars in 2010). This negative effect is unexpected as IMV adoption may increase household food expenditure with increases in dispensable income from sales of additional maize production. However, it may possibly reflect substitution effects between own-produced maize and purchased foods, where households who consume more own-produced maize may purchase less foods. The effects of IMV adoption on consumption of other own-produced foods is insignificant (γ_1^F), suggesting ignorable tradeoffs between IMV adoption and cultivation of other food crops. Despite possible substitution effects between own-produced maize and purchased foods, the total value of food and non-food consumption still increases as a result of IMV adoption. On the other hand, although all consumption types are expected to improve child nutrition outcomes, only consumption of own-produced maize (γ_1^N) and other own-produced foods (γ_2^N) are significant. Contributions through purchased foods (γ_3^N) and purchased non-food items (γ_4^N) are insignificant, although both have positive signs as

of our direct interest.

expected.

The decomposition procedure presented in equations (13) and (14) is then implemented with estimated parameters. We focus only on significant coefficient estimates from the system of equations. For both HAZ and WAZ, an increase in own-produced maize consumption is the only established pathway through which IMV adoption affects child nutrition outcomes, as the effect of IMV adoption on own-produced maize consumption, (γ_1^N) and the effect of own-produced maize consumption on child nutrition (γ_1^M) are both statistically significant. The effects are computed to be 0.19 for HAZ and 0.10 for WAZ. As previous estimation suggests that a one kert increase of IMV area raises HAZ and WAZ by 0.26 and 0.18 standard deviations, respectively, the adoption-related increase in own-produced maize consumption explains almost 75% of the overall impacts on HAZ and more than 50% on WAZ. The other three pathways are not statistically validated as some coefficients are found insignificant in each mechanism. We therefore conclude that the impacts of IMV adoption on child nutrition outcomes are largely realized through consumption increases of own-produced maize.

3.6. Concluding remarks

This paper contributes to the literature as a first empirical investigation on the causal linkages of the IMV adoption on child nutrition outcomes using household survey data from rural Ethiopia. It is found that IMV adoption has positive overall impacts on child nutrition outcomes, measured both in HAZ and WAZ. Such impacts are largest among children with poorest nutrition outcomes as estimated by quantile IV regressions. Further, multiple possible pathways linking IMV adoption and child nutrition are explored through the combination of system of equations estimation and a decomposition approach. For both HAZ and WAZ, the major channel through which IMV adoption enhances child nutrition is found to be consumption increase of own-produced maize.

Our results lead to several policy implications. First, IMV maize adoption not only enhances farm household's economic wellbeing, as found in previous literature, but also reduces child malnutrition. This study first explores and confirms this relationship, which is important as it provides increased evidence for CGI impacts beyond productivity and economic benefits. Though experimental methods such as RCTs are not appropriate to assess child nutrition impacts of IMVs already diffused for decades, our innovative methods used here have uncovered reasonably strong evidence of causality. Second, we find that the largest nutrition-enhancing impacts of IMVs occur among children with poorest nutrition outcomes, which is of practical value for policy makers and development agencies. Child malnutrition can be reduced if the poorest nutrition outcomes are improved; adoption needs to be promoted among the poor. IMV adoption benefits some of the neediest members of society. Policies that facilitate IMV adoption should be enhanced, with possible focus on improving farmers' access to seeds, inputs, credits, insurance and information. Third, as consumption increase of own-produced maize is found to be the major pathway through which IMV adoption improves child nutrition, efforts to foster home consumption of staple foods, such as improvement in food storage technologies, may be of practical value, especially those who are poor and food insecure.

References

Akuamoa-Boateng, A. 2002. Quality Protein Maize: Infant Feeding Trials in Ghana. Ghana Health Service, Ashanti, Ghana.

Alderman, H., J. Hoddinott, and B. Kinsey. 2006. Long term consequences of early childhood malnutrition. *Oxford Economic Papers* 58 (3): 450-474

Alene, A. D., Coulibaly, O., 2009. The impact of agricultural research on productivity and poverty in sub-Saharan Africa, *Food Policy* 34, 198-209.

Amemiya, T. 1982. Two stage least absolute deviations estimators. *Econometrica* 50, 689-711.

Beegle, K., C. Carletto, and K. Himelein. 2012. Reliability of recall in agricultural data. *Journal of Development Economics* 98: 34-41.

Behrman. 1988. Nutrition, health, birth order and seasonality. *Journal of Development Economics* 28: 43-62.

Behrman, J., H. Alderman, and J. Hoddinott. 2004. Hunger and malnutrition. In L. Bjorn, ed. *Global crises, global solutions*. Cambridge, UK: Cambridge University Press.

Berger, L.M., J. Hill, and J. Waldfogel. 2005. Maternity leave, early maternal employment and child health and development in the US. *The Economic Journal* 115: F29-F47.

Case, A., D. Lubotsky, and C. Paxson. 2002. Economic status and health in childhood: the origins of the gradient . *American Economic Review* 92: 1308-1334

Chamberlin. J., and E. Schmidt. 2012. Ethiopian agriculture: a dynamic geographic perspective. In P. Dorosh and S. Rashid, ed. *Food and Agriculture in Ethiopia: Progress and Policy Challenges*. Philadelphia PA: University of Pennsylvania Press.

Currie, J., and N. Cole. 1993. Welfare and child health: the link between AFDC participation and birth weight. *American Economic Review* 83: 971-985.

Evenson, R. E., and D. Gollin. 2003. *Crop Variety Improvement and Its Effect on Productivity: The impact of international agricultural research*. Wallingford, UK: CABI Publishing.

Garg. A., and J. Morduch. 1998. Sibling rivalry and the gender gap: evidence from child health outcomes in Ghana. *Journal of Population Economics* 11: 471-493.

Glewwe, P., and H. G. Jacoby. 1995. An economic analysis of delayed primary school enrollment in a low income country: the role of early childhood nutrition. *The Review of Economics and Statistics* 77(1): 156-169

Glewwe, P. 1999. Why does mother's schooling raise child health in developing countries? evidence from Morocco. *Journal of Human Resources* 34: 124-159.

Glewwe, P., and E. A. Miguel. 2007. The impact of child health and nutrition on education in less developed countries, In T. P. Schultz and J. A. Strauss, ed. *Handbook of Development Economics*, Volume 4. Elsevier: 3561-3606

Gunaratna, N.S., H. de Groote, P. Nestel, K.V. Pixley, and G.P. McCabe. 2010. A meta-analysis of community-based studies on quality protein maize. *Food Policy* 35: 202-210.

Hansen, L.P. 1982. Large sample properties of generalized method of moments estimators. *Econometrica* 50: 1029–1054

Hotz, C., C. Loechl, A. de Brauw, P. Eozenou, D. Gilligan, M. Moursi, B. Munhaua, P. van Jaarsveld, A. Carriquiry, and J. V. Meenakshi. 2012. A large-scale intervention to introduce orange sweet potato in rural Mozambique increases Vitamin A intakes among children and women. *British Journal of Nutrition* 108(1): 163-176.

Karanja, D.D., M. Renkow, and E.W. Crawford. 2003. Welfare effects of maize technologies in marginal and high potential regions of Kenya. *Agricultural Economics* 29: 331–341.

Kassie, M., B. Shiferaw, and G. Muricho. 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development* 39: 1784-1795.

Kleibergen, F., and R. Paap. 2006. Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics* 127: 97–126.

Low, J.W., M. Arimond, N. Osman, B. Cunguara, F. Zano, and D. Tschirley. 2007. A food-based approach introducing orange-fleshed sweet potatoes increased Vitamin A intake and serum retinol concentrations in young children in rural Mozambique. *Journal of Nutrition* 137(5): 1320-1327.

Maredia, M. K., D. Byerlee, and P. Pee. 2000. Impacts of food crop improvement research: evidence from sub-Saharan Africa, *Food Policy* 25, 531-559.

Mekonnen, A. 1999. Rural household biomass fuel production and consumption in Ethiopia: a case study . *Journal of Forest Economics* 5: 69-97

Moyo, S., G.W. Norton, J. Alwang, I. Rhinehart, and M. Deom. 2007. Peanut research and poverty reduction: impacts of variety improvement to control peanut viruses in Uganda. *American Journal of Agricultural Economics* 89: 448-60.

Reis, M. 2012. Food insecurity and the relationship between household income and children's health and nutrition in Brazil. *Health Economics* 21: 405–427.

Schneider, K., and L. Anderson. 2010. Yield gap and productivity potential in Ethiopian agriculture: staple grains and pulses. Evans School Policy Analysis and Research. EPAR

Brief No. 98. University of Washington.

Shiferaw, B., M. Smale, H. J. Braun, E. Duveiller, M. Reynolds, and G. Muricho. 2013. Crops that feed the world 10. Past successes and future challenges to the role played by wheat in global food security. *Food Security* 5, 291-317.

Singh, I., L. Squire, and J. Strauss. 1986. Methodological Issues. In I. Singh, L. Squire, and J. Strauss, eds. *Agricultural Household Models: Extensions, Applications and Policy.* Baltimore: Johns Hopkins University Press.

Skoufias, E. 1998. Child health during the economic transition in Romania. *World Development* 26(11): 2045-2056.

Strauss, J. 1986. The Theory and Comparative Statics of Agricultural Household Models: A General Approach. In I. Singh, L. Squire, and J. Strauss, eds. *Agricultural Household Models: Extensions, Applications and Policy.* Baltimore: Johns Hopkins University Press.

Thomas, D., V. Lavy, and J. Strauss. 1996. Public policy and anthropometric outcomes in the Côte d'Ivoire. *Journal of Public Economics* 61: 155-192.

Thomas, D., and J. Strauss. 1992. Prices, infrastructure, household characteristics and child height. *Journal of Development Economics* 39: 301-331.

Thomas, D., J. Strauss, and M-H. Henriques. 1991. How does mother's education affect child height? *Journal of Human Resources* 26: 183-211.

UNICEF. 2013. *Improving child nutrition: the increasing imperative for global progress.* United Nations International Children’s Fund, New York, NY.

Wooldridge, J. M. 1995. Score diagnostics for linear models estimated by two stage least squares. In G. S. Maddala, P. C. B. Phillips, and T. N. Srinivasan, eds. *Advances in*

Econometrics and Quantitative Economics: Essays in Honor of Professor C. R. Rao. Oxford: Blackwell Publishing.

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.

Zeng, D., J. Alwang, G.W. Norton, B. Shiferaw, M. Jaleta, C. Yirga. 2013. Ex-post impacts of improved maize varieties on poverty in rural Ethiopia. Diffusion and impact of improved varieties in Africa (DIIVA) - Objective 3 Report. Virginia Tech: Blacksburg, VA and CIMMYT: Nairobi, Kenya.

Table 3.1. Descriptive Statistics of Relevant Variables (n=791)

Variable	Mean	Std. Dev.
Total maize area (kert[1])	3.608	2.763
Adopting area (with IMVs, kert)	1.843	2.563
Total land holding (kert)	8.218	6.115
Household (HH) size	7.074	2.363
Head gender (M=1; F=0)	.975	.158
Head age (years)	38.74	10.64
Head education (years)	2.886	3.195
Head marital status (married=1; other=0)	.976	.153
Total household assets (100 Ethiopian Birrs, ETB[2])	169.2	413.7
Total household off-farm income (100 ETB)	41.17	99.45
Toilet (have a private toilet=1; other=0)	.817	.387
Piped water (yes=1; no=0)	.338	.473
Adoption history (longer than child age=1; not=0)	.726	.342
HH consumption of own-produced maize (100 ETB)	23.50	17.60
HH consumption of other produced foods (100 ETB)	69.93	45.60
HH food expenditure (100 ETB)	156.8	110.6
HH non-food expenditure (100 ETB)	91.31	151.7
Maize price (ETB/kg)	2.993	.968
Teff price (ETB/kg)	6.060	1.223
Wheat price (ETB/kg)	4.763	.915
Barley price (ETB/kg)	3.732	1.246
Maize seed price (ETB/kg)	3.647	1.664
Fertilizer price (ETB/kg)	7.405	.749
Soap price (ETB/bar)	5.064	.869
Child gender (M=1; F=0)	.504	.500
Age of children under age 5 (month)	31.70	17.54
No. of siblings of children under age 5	1.854	.821
Years known the IMV	6.37	5.65
Temporary seed supply disruption (yes=1; no=0)	.382	.399
Distance to the nearest seed dealer (walking minutes)	53.36	52.66

[1] 1 kert = 0.25 hectares.

[2] Daily average exchange rate is 1 USD = 14.38 ETB in 2010.

Table 3.2. IV-GMM Estimation of Overall Child Nutrition Impacts (n = 1,216)[1]

	HAZ	WAZ
Adopting area	.257*** (.083)	.176*** (.054)
Total maize area	.019 (.134)	-.043 (.087)
Total land	-.040 (.043)	-.034 (.026)
Child gender	-.113 (.127)	-.039 (.065)
Child age	-.053*** (.012)	-.029*** (.006)
Child age square	.004*** (.001)	.003*** (.001)
Siblings	-.122** (.053)	-.079** (.032)
Household size	-.094 (.064)	.019 (.023)
Head gender	.638** (.305)	.155 (.292)
Head age	.013 (.035)	.010 (.024)
Head education	.064*** (.021)	.038** (.018)
Head marriage	-.030 (.294)	-.236 (.187)
Total assets	.003*** (.001)	.011*** (.004)
Total off-farm income	.027 (.031)	.004 (.003)
Adoption history	.227** (.103)	.147* (.076)
Private toilet	.141 (.123)	.043 (.068)
Piped water	-.082 (.151)	.154 (.105)
Maize price	.033 (.074)	-.025 (.049)
Teff price	-.056 (.087)	.037 (.047)
Wheat price	.113 (.075)	-.029 (.038)
Barley price	.017 (.052)	-.019 (.022)
Maize seed price	-.065 (.051)	-.024 (.043)
Fertilizer price	-.041 (.085)	-.027 (.051)
Soap price	.085 (.119)	.055 (.062)
Region: Amhara	.313 (.512)	.446 (.530)
Region: Oromia	.379 (.519)	.296 (.350)
Region: SNNPR	.586 (.657)	.613 (.512)
Constant	-4.63 (1.12)	-2.42 (.781)
Identification tests		
Underidentification[2]	27.12 (.000)	27.12 (.000)
Weak identification[3]	21.86	21.86
Overidentification[4]	1.621 (.409)	2.622 (.259)

[1] Standard errors reported in parentheses. ***, **, * indicate 1%, 5% and 10% significance, respectively.

[2] Kleibergen-Paap (2006) rank LM test is performed. p-values are reported in parentheses.

[3] Kleibergen-Paap (2006) rank Wald F test is performed.

[4] Hansen's (1982) J test is performed. *p*-values are reported in parentheses.

Table 3.3. GMM 3SLS Estimation of Partial Effects (n = 1,216)[1]

	HAZ	WAZ
γ_1^M	2.94^{***} (.753)	2.94^{***} (.753)
γ_1^F	-.337 (.354)	-.337 (.354)
γ_1^R	-2.28^{***} (.786)	-2.28^{***} (.786)
γ_1^C	$.731^{**}$ (.341)	$.731^{**}$ (.341)
γ_1^N	$.063^{***}$ (.022)	$.033^{**}$ (.015)
γ_2^N	$.023^{**}$ (.008)	$.009^{***}$ (.003)
γ_3^N	.007 (.012)	.003 (.007)
γ_4^N	.001 (.004)	.006 (.005)

[1] Standard errors reported in parentheses. ***, **, * indicate 1%, 5% and 10% significance, respectively. Full estimation results are available upon request.

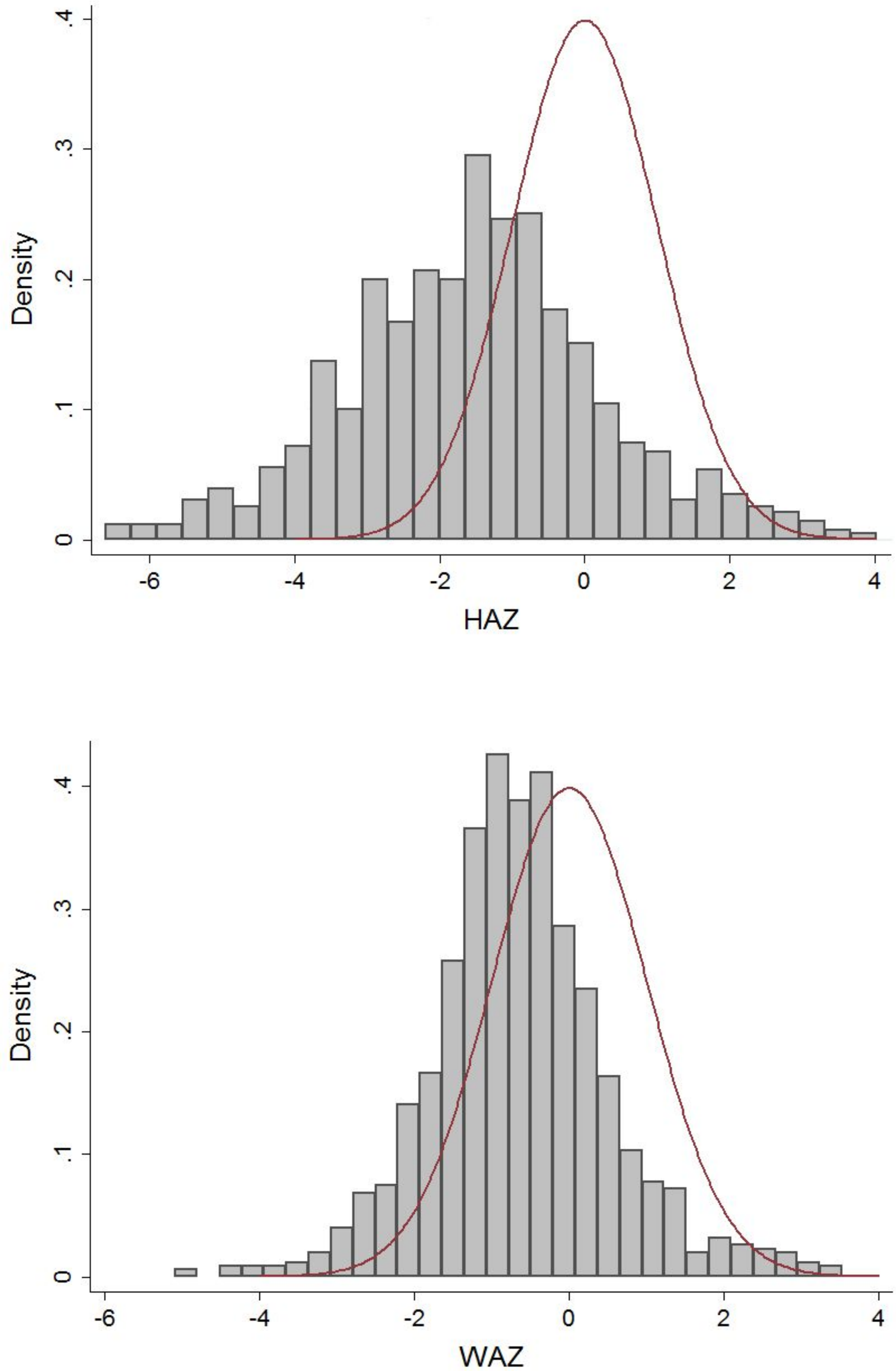

Figure 3.1. HAZ and WAZ of surveyed children (n = 1,216)

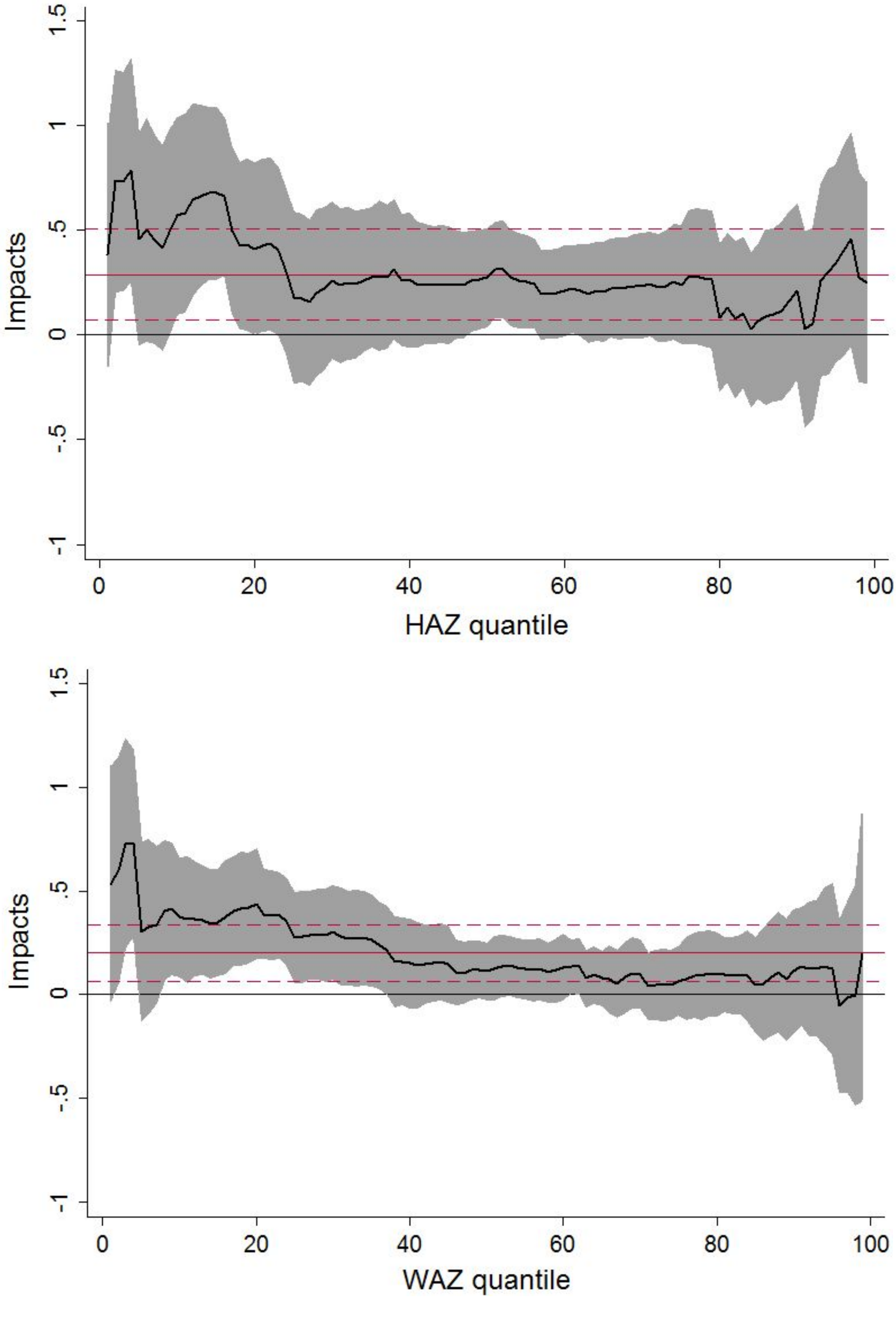

Figure 3.2. Quantile impacts on HAZ and WAZ (n = 1,216)[1]

[1] 95% point-wise confidence interval of quantile IV estimates are presented in gray areas. The mean estimate is presented as a solid line, with its 95% confidence interval presented as two dotted lines.

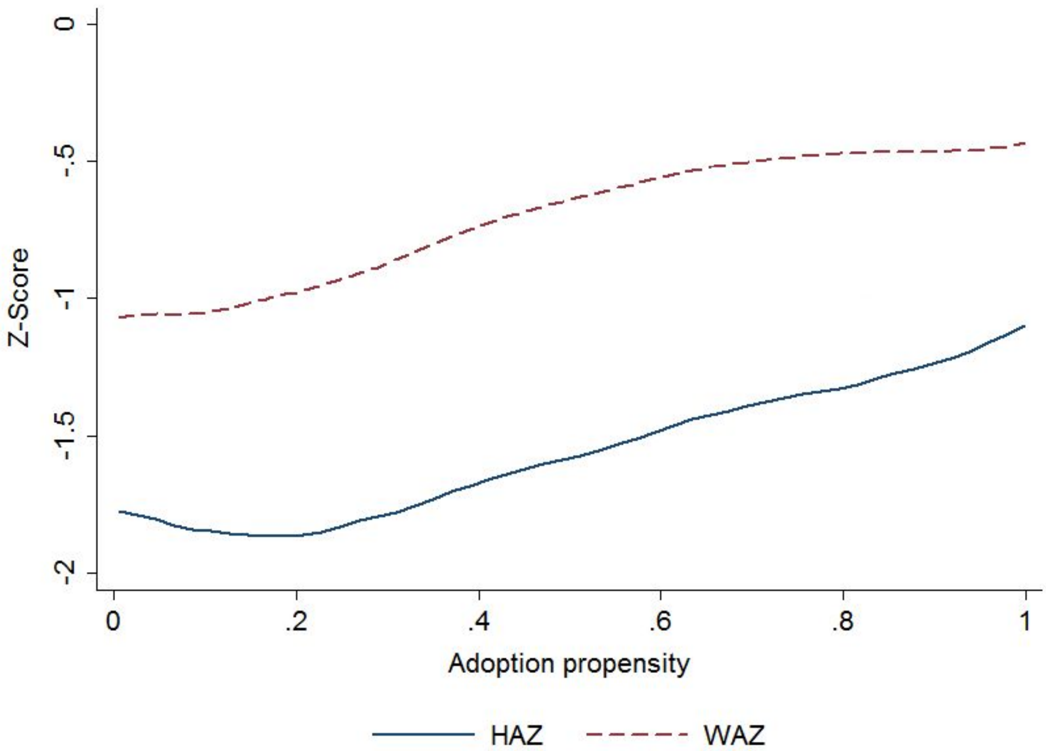

Figure 3.3. Child nutrition outcomes by adoption propensity

Chapter 4

Essay 3: Perception and Adoption of Improved Maize Varieties in Ethiopia

4.1. Introduction

Agricultural research on crop genetic improvement (CGI) has led to thousands of improved crop varieties in the developing world that have contributed to large increases in crop production worldwide (Evenson and Gollin, 2003; Renkow and Byerlee, 2010). The distribution of productivity gains, however, is uneven among producers. Benefits of technologies are directly felt through adoption, but welfare impacts for adopters and non-adopters can oppose each other, leading to increasing gaps between these groups (de Janvry and Sadoulet, 2002; Zeng et al., 2013). Understanding farmer's adoption behavior is therefore a first step in correctly assessing the multidimensional welfare impacts of CGI research. Such information is of great importance in assisting policy makers and funders to effectively allocate investments in agricultural research in the future.

Previous literature has focused on identification of factors that affect agricultural technology adoption in developing countries. These factors include plot-level factors such as land tenure, acreage and soil fertility (Deininger and Jin, 2006; Abdulai et al., 2011), household-level factors such as wealth (Langyingtuo and Mungoma, 2008), education (Lin, 1991), risk attitude and credit constraints (Croppenstedt et al., 2003), and community-level factors such as social network and learning (Munshi, 2004; Conley and Udry, 2010). Most adoption studies use observed characteristics to explain adoption, while the roles of unobserved characteristics such as farmers' perceptions remain largely unknown due to data limitations. Recent studies have also explored how technology traits affect the adoption decision (Batz et al., 1999; Useche et al., 2009). However, technology traits may be perceived differently by individual farmers, and accurate measurement of these traits can be extremely difficult, especially in an ex-post setting (Useche et al., 2013).

A few studies have taken into consideration the effects of farmers' perceptions of technology traits on adoption decision in Sub-Saharan Africa (Adesina and Zinnah, 1993; Adesina and Baidu-Forson, 1995; Negatu and Parikh, 1999; Legese et al., 2011; Lunduka et al., 2012). In these studies, farmers' subjective assessments of technology traits are directly employed to explain the adoption decision. However, these assessments can be endogenous as they may be correlated with other unobserved characteristics that also affect adoption decision, such as the farmer's ability and experience using the technology. Also, in a cross-sectional setting, farmers' perceptions of technology traits may have been updated through cropping practices and learning in the surveyed season, and cannot logically affect the adoption decision made at the beginning of that season. A a result, causal linkages established in this manner may be problematic.

A few recent studies have used panel data to study technology adoption. For example, Suri (2011) uses panel data in Kenya to investigate how profitability affects adoption of hybrid maize, where switching adoption behavior between adoption and non-adoption receives specific attention. However, Suri's data was collected over a long period of time with multiple-year gaps between consecutive rounds of the survey. It cannot accurately capture switching in varietal choices which may occur with greater frequency. Although panel data over sequential seasons may provide a solution, data collection can be extremely resource-demanding and such data are therefore rarely available.

This paper contributes to the literature by using a unique cross-sectional household survey to investigate how perceptions of crop traits affect farmers' wilingness to adopt improved maize varieties (IMVs). In the survey, farmers were asked not only about the adoption decision made in the current cropping season but also their adoption intention of the same IMV in the future, which facilitates our use of farmers' current yield perceptions to model their willingness to adopt that IMV. A random utility framework is employed allowing incorporation of farmers' perceptions into the adoption decision process. A mixed logit procedure is implemented to model farmer's adoption intention, where perceptions of key varietal traits are first identified, and then instrumented using a control function approach to account for potential endogeneity. Perceived yield is found to be the most important trait affecting farmers' adoption intention. Further, yield perceptions among previous adopters appear to be affected by within-village peer effects rather than objective varietal performance that the farmer experiences. Several policy implications concludes the paper.

4.2. Maize cultivation in Ethiopia

Maize is a major cereal and staple food in Ethiopia, and accounts for the largest share of production by volume and is produced by more farms than any other crop (Chamberlin and Schmidt, 2012). From the 1960s to 2009, the dietary calorie and protein contributions of maize in Ethiopia doubled to around 20% and 16%, respectively (Shiferaw et al., 2013). Like many countries in Sub-Saharan Africa, Ethiopia has observed significant increases in maize productivity due to CGI research (Zeng et al., 2013). During the 2009/10 production year, Ethiopia produced 3.89 million tons of maize on 1.77 million hectares of land (Central Statistical Agency, 2010), giving an average productivity of 2.20 tons per hectare, which is the highest of all cereal crops in that year.

In the last four decades, more than 40 IMVs have been developed and released through joint efforts from the Ethiopian Institute of Agricultural Research and the International Maize and Wheat Improvement Center. IMVs include hybrid varieties and improved open-pollinated varieties (OPVs). Hybrids have the highest yield, but require 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 cropping seasons. Many OPVs are developed for challenging conditions (i.e. droughts, pests) and under circumstances where seed markets are underdeveloped or missing. IMV adoption in Ethiopia varies across agroecological regions. There is no dominant variety, while hybrids are generally more popular than OPVs, and both hybrids and OPVs are better known and more widely adopted in areas with higher maize potential (Jaleta et al., 2013).

Several studies have investigated the determinants of the IMV adoption in Ethiopia. Feleke and Zegeye (2006) use survey data from Southern Ethiopia and find adoption to be significantly affected by number of adult laborers, education of household head, distance to market, and access to resources such as extension agencies and credit. Tura et al. (2010) focus on Central Ethiopia where household labor, assets, credit access and membership in farmer cooperatives affect adoption, while several factors such as education, off-farm labor supply and extension visits are associated with continued use after first adoption. Legese et al. (2011) investigate the adoption of drought tolerant maize varieties in drought-prone areas of Ethiopia and find that factors such as gender of household head and extension visits have different impacts on maize adoption across different wealth groups. These studies provide insights into maize varietal adoption in Ethiopia. However, they generally employ small household surveys from small regions or agroecological zones, and are not nationally representative. They also fail to identify the role of farmers' perceptions of IMV traits in IMV adoption.

4.3. Model

Maize farmers make IMV adoption decisions for each cropping season, a repeated choice. In our survey, farmers were asked not only about the adoption decision in the current cropping season but also their intention to adopt the same IMV in the future. Each farmer's IMV adoption decision can be viewed as sequentially made in the two-period timeframe. However, our study differs from the sequential adoption literature where different technologies, or different components of a technology package, are gradually adopted over time (Leathers and Smale, 1991; Ersado et al., 2004; Aldana et al., 2011). Also, unlike most sequential adoption studies that cover multiple periods, our analysis is implemented in a cross-sectional setting as no information on yield perceptions prior to the current cropping season was available.

At the end of the current cropping season (period *t*), farmer *i* aims to select a maize variety *V* for the next cropping season (period *t*+1), to maximize a utility, $U_{i,t+1}^{V}$. $U_{i,t+1}^{V}$ is a assumed to be a function of expected maize profit, $\pi_{i,t+1}^{V}$, and an additive random disturbance, $\varepsilon_{i,t+1}^{V}$, that follows an i.i.d. extreme value distribution:

$$U_{i,t+1}^{V} = \pi_{i,t+1}^{V} + \varepsilon_{i,t+1}^{V} \qquad (1)$$

$\pi_{i,t+1}^{V}$ is a function of prices for both inputs and expected maize output, $P_{i,t+1}^{V}$, maize yield, $Y_{i,t+1}^{V}$, inputs, $I_{i,t+1}^{V}$, household characteristics, $H_{i,t+1}$ and physical environments, $E_{i,t+1}$. All arguments except $H_{i,t+1}$ and $E_{i,t+1}$ are considered variety-specific. Specifically, price can vary among varieties and households as it may reflect certain varietal traits that are not directly observable (e.g. nutrition value). The expected profit is therefore written as:

$$\pi_{i,t+1}^{V} = \pi_{i,t+1}^{V}(P_{i,t+1}^{V}, Y_{i,t+1}^{V}, I_{i,t+1}^{V}, H_{i,t+1}, E_{i,t+1}) \qquad (2)$$

$H_{i,t+1}$ and $E_{i,t+1}$ are assumed not to vary between periods *t* and *t*+1, which makes sense as there are two maize cropping seasons in a year, and each period is comparatively short.Ignoring inflation issues, $P_{i,t+1}^{V}$ is equal to its counterparts in period *t*, $P_{i,t}^{V}$, if no *a priori* reason to expect any change exists, which we implicitly assume.

The expected maize profit in period t+1 thus can be conveniently written as:

$$\pi^V_{i,t+1} = \pi^V_{i,t+1}(P^V_{i,t}, Y^V_{i,t+1}, I^V_{i,t+1}, H_{i,t}, E_{i,t}) \qquad (3)$$

In the sense of a production function , $Y^V_{i,t+1}$ contains arguments such as $I^V_{i,t+1}$, $H_{i,t+1}$ and $E_{i,t+1}$. Inputs are all endogenous, determined jointly by $H_{i,t+1}$, $E_{i,t+1}$ and farmer *i*'s perceptions of variety traits, $K^V_{i,t}$, which are updated in period *t*. It makes sense that perceptions play a role in input decisions. For example, perceived high yield potential may urge fertilizer use, while perceived drought tolerance or pest resistance may relax related risk mitigation practices. Thus, maize yield in period t+1 can be expressed as:

$$Y^V_{i,t+1} = Y^V_{i,t+1}[I_{i,t+1}(P^V_{i,t}, H_{i,t+1}, E_{i,t+1}, K^V_{i,t}), H_{i,t+1}, E_{i,t+1}] = Y^V_{i,t+1}(P^V_{i,t},, H_{i,t}, E_{i,t}, K^V_{i,t}) \qquad (4)$$

where the second equation is the envelope result derived based on the choice nature of inputs and assumptions discussed above.

The farmer will adopt variety *V* in period t+1 if it yields higher utility than any other variety, that is, $U^V_{i,t+1} > U^{-V}_{i,t+1}$. The adoption intention based on the random utility framework specified in equation (1) can be further specified in the following function:

$$V_{i,t+1} = V_{i,t+1}(P^V_{t+1}, H_{i,t+1}, E_{i,t+1}, K^V_{i,t}, \varepsilon^V_{i,t+1}, \varepsilon^{-V}_{i,t+1}) = V_{i,t+1}(P^V_t, H_{i,t}, E_{i,t}, K^V_{i,t}, \varepsilon^V_{i,t+1}, \varepsilon^{-V}_{i,t+1}) \quad (5)$$

Farmer *i*'s perceptions, $K^V_{i,t}$, are likely endogenous as it may be correlated with unobservables, such as his/her ability or experience, that also affect $V_{i,t+1}$ in unknown ways. Specifically, farmer *i*'s perceptions of variety *V* is possibly affected by other farmers' (-*i*) perceptions of the same variety, $K^V_{-i,t}$, through informal learning within his/her social network (Munshi, 2004; Conley and Udry, 2010). Prices in period *t* that reflects traits not directly observable, P^V_t, observed household characteristics, $H_{i,t}$, physical environments, $E_{i,t}$, all affect farmer *i*'s perceptions, as well as a random error that captures unobserved heterogeneity among farmers, $\upsilon^V_{i,t}$. In this sense, the perception formation process is expressed as:

$$K^V_{i,t} = K^V_{i,t}(K^V_{-i,t}, P^V_t, H_{i,t}, E_{i,t}, \upsilon^V_{i,t}) \tag{6}$$

Equations (5) and (6) form a structural simultaneous equations model that leads to our empirical specification and estimation. Specifically, it suggests the use of other farmers' perceptions, $K^V_{-i,t}$, as the excluded instrument variable (IV) to address the endogeneity of farmer *i*'s perceptions when he/she determines $V_{i,t+1}$. $K^V_{-i,t}$ should satisfy the exclusion restriction as other farmers' perceptions should not be correlated with farmer *i*'s unobserved characteristics such as ability and experience, and thus would not affect his/her adoption intention except through perceptions.

As IMV adoption is a repeated choice for each cropping season, we specify a mixed logit model, also known as random coefficient logit, to investigate farmers' adoption intention in period *t*+1 using their perceptions updated and reported in period *t* (Train, 1986). Unlike standard logit or conditional logit models, the mixed logit model relaxes the undesirable assumption of independence of irrelevant alternatives (IIA). Empirically, specify equation (1) in linear form (period subscripts suppressed):

$$U^V_i = X^V_i \beta_i + \varepsilon^V_i \tag{7}$$

where X^V_i is the vector containing arguments of $\pi^V_{i,t+1}$, namely P^V_t, $H_{i,t}$, $E_{i,t}$ and $K^V_{i,t}$ (with $Y^V_{i,t+1}$ and $I^V_{i,t+1}$ dropped due to envelope results), and β_i is a individual- specific random vector of coefficients with density $f(\beta)$. As β_i can be further decomposed as the sum of its mean, $\overline{\beta}$, and individual deviations from the mean, $\widetilde{\beta}_i$. The unobserved random portion of utility, $X_i^V \widetilde{\beta}_i + \varepsilon_i^V$, can reflect heterogeneous individual preferences and may be arbitrarily correlated over choices. For each IMV, the decision whether to adopt it (*V*) or not (-*V*) is binary. Based on equation (7), the adoption rule of variety *V* can be written as:

$$P_i^V = \Pr(\varepsilon_i^V - \varepsilon_i^{-V} > X_i^{-V}\beta_i - X_i^V\beta_i) = \int \frac{\exp(X_i^V\beta_i)}{1+\exp(X_i^V\beta_i)} f(\beta)d\beta \qquad (8)$$

Estimation usually involves partitioning β_i into fixed parameters and random parameters. Fixed parameters follow degenerate distributions (with no variation). By making assumptions about the distributions of the random parameters (usually multivariate normal), the probability in equation (8) can be empirically simulated by repeated random draws of β_i from $f(\beta)$ (Train, 2003):

$$P_i^V = \frac{1}{N}\sum_{n=1}^{N}\frac{\exp(X_i^V\beta_i^n)}{1+\exp(X_i^V\beta_i^n)} \qquad (9)$$

A control function (CF) approach is used to address endogeneity as X_i^V contains endogenous arguments K_i^V (Fox et al., 2012). This approach is advantageous in nonlinear models as compared to traditional instrumental variable (IV) techniques (Wooldridge, 2007). The idea behind the CF approach is to derive a proxy that captures the dependency of K_i^V on ε_i^V , which then enters the model to directly control for the dependency. Commonly used CF is the residual estimated by running OLS regression of the endogenous variable on all exogenous covariates and excluded instruments, which in our case would be $\hat{\upsilon}_i^V$ from equation (6). If such dependency is properly controlled for, the remaining variation in K_i^V will be independent of the error and standard estimation approaches is still consistent (Petrin and Train, 2009).

Empirical estimation in our case includes three steps. First, we assume equation (6) takes linear form and estimate it using OLS regression to obtain the predicted error term, $\hat{\upsilon}_i^V$, where K_i^{-V} serves as the excluded IV. Second, the CF $\hat{\upsilon}_i^V$ is added to equation (7) as a vector of explanatory variables. By assuming a multivariate normal distribution for the random parts of β_i, equation (7) is then estimated through approximation of the likelihood using adaptive Gaussian quadrature. Finally, as the procedure uses predicted values ($\hat{\upsilon}_i^V$) as regressors, bootstrapping is used to correct for standard errors (Camponovo and Otsu, 2011).

As perceptions of varietal traits may have formed in different ways, a unique excluded IV is applied to each trait, and $\hat{\upsilon}_i^V$ is obtained as a vector. Specifically, perceptions on each IMV trait of farmers living in the same village are employed as the IV to predict farmer *i*'s perception of the trait. Use of this information is justified since farmers learn of and about agricultural technologies through knowledge spillovers within social networks (Munshi, 2004; Conley and Udry, 2010). As other farmers' perceptions of IMV traits should not be correlated with unobserved characteristics of farmer *i* (e.g. ability, experience), they are not likely to affect farmer *i*'s adoption intention other than through affecting farmer *i*'s perceptions of those traits. Thus, these IVs should satisfy the exclusion restriction.

The explanatory variables in the mixed logit specification include prices (P^V), household characteristics (H_i), physical environments (E_i), farmer *i*'s perceptions (K_i^V), as well as the control functions ($\hat{\upsilon}_i^V$). Prices of IMV seeds and fertilizer, as well as maize output price, are included. Household characteristics include household size, total assets, total landholding, and the gender, age, education and marital status of household head. As financial constraints may negatively affect farmers' adoption motivation, also included is a dummy indicator that identify if a farmer has unmet credit needs in crop production in the past cropping season[9]. Physical environments contain factors that may affect adoption, including distances to the nearest main market, seed dealer and fertilizer dealer. Also included are a seasonal dummy and several regional dummies.

A few other explanatory variables are also included. First, the adoption decision of current season is included as a binary variable. Since it is also endogenous (correlated with some time-invariant unobservables such as farmer's ability), the control function approach is also applied with the excluded IV of the number of years that the farmer has been aware of the IMV. Second, interactions between current adoption decision and perception of each trait are also included. As discussed below, estimates of these interactive effects, together with the individual perceptions, facilitate our understanding of why some farmers' switching adoption behavior (entering adoption of current non-adopters and exiting adoption of current adopters).

To ease interpretation of regression results, the interaction terms are treated as fixed (Ai and Norton, 2003). Also fixed are regional dummies as they are not options for most households. All other coefficients are allowed to be random.

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[9] Some farmers do not need credit, while some others in need of credit can still successfully secure it. Thus, this dummy indicates if access to credit is a "real" constraint in maize production.

4.4. Data description

This study employs a recent survey of Ethiopian rural households conducted during 2009-2010. Four regions are included: Tigray, Amhara, Oromia, 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). The survey uses a stratified random sampling strategy that covers areas of varying maize potential, and is nationally representative.

A total of 1,072 farm households (farmers hereafter) are present in the survey with perceptions properly documented, from whom a total of 1,787 perception records of IMV traits are obtained (see below for detailed discussion), suggesting the average number of IMVs known to is 1.67. Detailed information on maize production, household characteristics and local infrastructure are captured in the questionnaire. Crop production practices such as choices of varieties, yields and inputs in the previous season are recalled by the farmer. Household characteristics include demographics, resource endowments, farm and non-farm assets and total land holding, and the age, gender, education and marital status of household head. Also reported are local infrastructure measures such as the access to market, various inputs and credit. Descriptive statistics of these characteristics are reported in Table 1.

In maize cropping practices, few plants are genetically pure as inbred lines are usually crossed through open pollination. Also, the yields of hybrids and OPVs observe minor differences in our data. For these reasons, varieties are only differentiated as either improved or local. As suggested by local breeding scientists, any hybrid variety ever recycled or an OPV recycled for more than three seasons are categorized as local.

As other farmers' perceptions are employed as IVs, our analytical procedure requires that there are at least two farmers who know of the same IMV in each village where the IMV is known, so that one farmer's perceptions can be instrumented by those of others. To satisfy these requirements, only 1,398 perception records from 960 households are included in the analysis, varieties including seven hybrids and five OPVs.[10] Characteristics of the 960 included households (knowers of popular IMVs) and the 112 excluded ones (knower of less popular IMVs) are also summarized in Table 1. Pairwise *t*-tests reveal little systematic difference between the household characteristics of these two groups (with only total maize area and distance to the nearest fertilizer dealer being marginally different). Therefore, the final data (1,398 perception records from 960 households) are representative of all maize farmers.

As adoption decision is trait-based and variety-specific, the 1,398 perception records serve as basic units in the analysis. IMV-specific adoption behavior, combining current adoption decision and willingness to adopt in the future, is reported in Table 2. Most IMV adopters grow just one improved maize variety, of whom a small portion (96 farmers) wish to cease adopting the reported IMVs. Non-adopters who wish to adopt IMVs in the future are interested in two of them on average. Three

[10] Hybrids include BH-660 (known to 534), BH-140 (known to 215), BH-540 (known to 176), Shone (known to 147), Tabor (known to 121), BH543 (known to 42) and Agar (known to 21) . OPVs include Awassa-511 (known to 45), Gibe (known to 29), Katumani (known to 27), Fetene (known to 24) and the Melkassa series (Melekassa-1, Melekassa-2 and Melekassa-4, known to 17).

fourth of the non-adopters are interested in adopting some IMVs later, while 81 farmers are not interested in some IMVs even if they know these IMVs.

Perceived IMV traits recorded in the survey include grain yield, drought tolerance, water-logging tolerance, disease resistance, pest resistance, early maturity, storability, grain size, taste and grain price.[11] The original assessments of each IMV trait as compared to local varieties are recorded on a five-point rating scale, which indicates, from 1 to 5, very poor, poor, average, good and very good. An overall varietal score of each IMV is also recorded for each farmer on the same scale. To facilitate econometric estimation, these trait-specific perceptions and the overall varietal score are then grouped into binary scores that categorize each perceived trait as either better than that of local varieties (if evaluated as very good or good), or similar to or even worse than over that of local varieties (if evaluated as average, poor and very poor). Table 3 describes these trait-specific perceptions and the overall varietal score in the final data. Among all IMV traits, most farmers are satisfied with grain yield, taste, early maturity, grain price and grain size.

4.5. Results

Although several varietal traits are present in each perception record, it is likely that farmers value only some of them. Thus, perceptions of minor traits may not significantly affect IMV adoption. Moreover, farmers' perceptions of different IMV traits can be correlated and therefore naive incorporation of all of them in the adoption

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[11] Grain price is not a physical trait, but may affect some unobserved traits such as nutrition value.

modeling may obscure individual effects of certain traits. As a result, it is necessary to understand how farmers rank the relative importance of these IMV traits.

The identification of key perceived traits is facilitated by the utilization of the overall varietal score evaluated by farmers. Previous literature has investigated the determinants of farmers' perceptions in cropping practices (e.g. Gebremedhin and Swinton, 2006). Using a similar procedure, the overall varietal score is regressed against observed household and infrastructure characteristics as well as all all trait-specific perceptions (measured on binary scales). Then the key perceived traits are identified as those with significant partial effects (coefficients). A linear model with the binary dependent variable of overall varietal score, or the linear probability model (LPM, Angrist, 2001), is first run to obtain consistent estimates. A probit model is also estimated to better capture the binary nature of the overall varietal score. In both models, endogeneity of perceptions are accounted for again using CFs estimated using the average evaluation of the same trait by other farmers within the same village as excluded IVs.[12] In this way, key perceived traits that most likely affect IMV adoption are identified and to be included in further analysis.

Table 4 provides estimation results. The CFs of seven out of ten perceived traits are found to be significant coefficients, suggesting potential endogeneity of these perceptions. Among all perceived traits, only grain yield, disease resistance, storability, grain price and taste are found to significantly affect the overall varietal score in both LPM and probit models. Thus, the adoption analysis below considers these five

[12] The control function estimator coincides with standard 2SLS estimator in the linear probability model.

perceived traits while ignoring those without significant effects on the overall varietal score. Besides, little systematic linkage is found between observed characteristics and the overall varietal score.

The mixed logit model above is then estimated with key perceived traits identified above. As discussed above, the interactive terms and regional dummies are treated as fixed, and all other coefficients are random. Table 5 shows estimation results. Marginal effects of interactive terms are computed following Ai and Norton (2003), while marginal effects of other terms are obtained using the delta-method. The estimated standard deviations of most coefficients (except current adoption status, prices, seasonal dummy and household head gender) are significant, confirming the presence of cross-individual heterogeneity in preferences regarding a number of factors. Our further estimation and model comparison also reject the simple logit model against the mixed logit procedure.

Among all perceived traits, grain yield is the foremost determinant of farmers' willingness to adopt the IMV in the future, with a marginal effect of 0.434 which is greater than the marginal effect of any other factor. This is quite intuitive as grain yield is probably the most valued trait that directly affects the maize profitability. Coefficient and marginal effect estimates of other perceptions are insignificant, but their standard deviations are all significant, suggesting varying preferences regarding these perceptions that balance each other out in our data.

Although it is tempting to expect a current adopter to be more likely to continue IMV adoption, such effect is found insignificant, though of a positive sign as expected.

In fact, this effect might have been partly captured by and attributed to the interactive terms between perceptions and current adoption status. The interactive effect between perceived yield and current adoption is again found to be of most importance, with a highly significant marginal effect of 0.246. Besides, the interactive effect between perceived price and current adoption also plays a role, but of a very small magnitude with marginal significance.

Further interpretation of the perception-related terms lies in their potential explanatory power for switching adoption behavior, including entering adoption of current non-adopters and exiting adoption of current adopters. Marginal effect estimate suggests that the adoption probability of farmers of positive yield perceptions is on average 0.434 higher than those of negative yield perceptions. Thus, better knowledge of IMVs may greatly increase the tendency that a current non-adopter adopts them in the future. It is also suggested that being a current adopter and of a positive yield perception increases the probability of future adoption of that IMV by 0.246. However, a current adopter of a negative yield perception may have a probability of adoption equally lower. These adopters may opt to stop adopting some IMVs if their yields are perceived poor. All these effects suggest the prominent role yield perception plays in farmers' adoption decision making, which has been neglected in most literature.

Besides perception-related terms, some observed characteristics also significantly affect farmers' willingness to adopt. As expected, adoption intention is positively correlated with observed maize market price and education of household head, and negatively correlated with seed price, distance to seed dealer and the existence of unmet credit need, the last two effects suggesting the importance of transaction costs and access to necessary resources IMV adoption. Farmers are found less likely to adopt in the long rainy season, which is unexpected and suggests the seasonal dummy might not be a very good measure as most farmers (93.9%) grow maize in the long rainy season. All the significant effects found here are of much smaller marginal effects as compared with those of yield perception and its interactive effect with current adoption behavior. It again suggests the importance of perceptions in adoption decision making, the ignorance of which may lead to severely biased and uninformative estimates.

As farmers' perceptions of grain yield is found to be the most important trait that affects their adoption intention, it is necessary to understand how such perception is formed. Of our specific interest is how actual maize yield, also reported in the survey, affects farmers' perceptions of grain yield, which finally affect their adoption behavior. Based on farmers' perceptions of IMV grain yield (1: better than local varieties, or 0: similar to or worse than local varieties) and their adoption decision in the current cropping season, farmers are grouped into four categories: current adopters with yield perception of 1, current adopters with yield perception of 0, current non-adopters with yield perception of 1, and current non-adopters with yield perception of 0. Per-hectare IMV yields are reported by current adopters, while per-hectare yields of local varieties are reported by current non-adopters, both of which are plot-based. These yields directly serve as an objective measure of varietal performance. Besides, a subjective counterpart is also constructed: the ratio of farmer *i*'s per-hectare yield over the average per-hectare yield all other farmers' in the same village who grow the same variety (the within-village yield ratio). Such ratio may affect farmer *i*'s perception of grain yield through possible peer effects through learning.

Table 6 describes the two measures of actual yield. For current adopters, though actual yields of those who consider IMV yields as better than local varieties appear to be higher than those who consider the opposite, such difference is not statistically significant. However, the average within-village yield ratios between these two groups of farmers do observe significant difference: current adopters who consider IMV yields as less attractive have observed significantly lower IMV yields than other villagers who grow the same IMV. Such discrepancy therefore suggests that farmers' yield perceptions are more likely to be affected by peer effects rather than the actual yields they have. On the other hand, for current non-adopters, their yield perceptions seem not to be affected by either actual yield or within-village yield ratio. Whatever perceptions these current non-adopters maintain on IMV yields, their local variety yields appear to be much lower than that of IMVs. Thus, better information should be provided to these farmers to encourage their adoption of more rewarding IMVs.

4.6. Concluding remarks

This paper contributes to the literature by explicitly modeling the impacts of perceptions on agricultural technology adoption, where perceptions on key IMV traits are first identified and then instrumented through a control function approach in the mixed logit procedure to account for endogeneity. It is found that a positive perception of maize yield significantly increases farmers' willingness to adopt, such effect being larger than that of any other factors included in our study. Yield perception is also a leading predictor of new adoption of current non-adopters and exiting adoption of current adopters. Thus, it is necessary for empirical studies to pay careful attention to farmers' perceptions in modeling agricultural technology adoption, the omission of which would severely bias estimation results.

It is further found that perceptions of IMV yields of current adopters are more likely to be affected by peer effects rather than their actual yields. Specifically, current adopters may consider IMVs as less attractive if their IMV yields are lower than their village peers, though their actual yields are not necessarily low if compared at broader (e.g. national) levels. Although only simple tests are employed to investigate such determination, such causal relationship is still logically concluded as farmers' yield perceptions cannot in turn affect either their actual yield or the within-village yield ratio.

Several important policy implications are worth discussion. First, it is of greater importance for agricultural development agencies to understand the role perceptions play in farmers' adoption decision making, through possible means such as enhanced communication between agricultural extension agencies and farmers, which would potentially improve the efficiency in adoption promotion. Second, as the perception of low grain yield discourages adoption, strategies such as well-targeted field demonstration possibly carried out in field days may provide useful information to farmers that helps them learn of IMV yields accurately, which should finally promote new and continued adoption. Third, as crop failures due to unpredicted shocks such as extreme climate can lead to misperceptions of crop performance, special assistance such as risk mitigation efforts need to be promoted at the same time IMV promotion takes place. Access to key resources such as seeds, credits and agricultural insurance should be improved to encourage continued adoption after bad seasons. With these policy implications, this study calls for further investigations on the roles perceptions play in agricultural technology adoption. In fact, farmers may value different traits of different technologies, improved understanding of which can be expected to synergize the adoption of one another, and help achieve higher welfare goals.

References

Abdulai, A., V. Owusu, R. Goetz. 2011. Land tenure differences and investment in land improvement measures: Theoretical and empirical analyses. *Journal of Development Economics* 96: 66-78.

Adesina, A.A., J. Baidu-Forson. 1995. Farmers' perceptions and adoption of new agricultural technology: evidence from analysis in Burkina Faso and Guinea, West Africa. *Agricultural Economics* 13: 1-9.

Adesina, A.A., M.M. Zinnah. 1993. Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone. *Agricultural Economics* 9: 297-331.

Ai, C., E.C. Norton. 2003 Interactive terms in logit and probit models. *Economics Letters* 80: 123-129.

Aldana, U., J.D. Foltz, B.L. Barham, P. Useche. 2011. Sequential adoption of package technologies: the dynamics of stacked trait corn adoption. *American Journal of Agricultural Economics* 93: 130-143.

Angrist, J. 2001. Estimation of limited dependent variable models with dummy endogenous regressors: simple strategies for empirical practice." *Journal of Business and Economic Statistics* 29: 2-15.

Batz, F.-J., K.J. Peters, W. Janssen. 1999. The influence of technology characteristics on the rate and speed of adoption. *Agricultural Economics* 21: 121-130.

Camponovo, L., T. Otsu. 2011. Robustness of bootstrap in instrumental variable regression. Cowles Foundation Discussion Paper No. 1796. Available at SSRN: http://ssrn.com/abstract=1822267

Central Statistical Agency. 2010. 2010 National Statistics (Abstract). Addis Ababa.

Chamberlin. J., E. Schmidt. 2012. Ethiopian agriculture: a dynamic geographic perspective. In P. Dorosh and S. Rashid, eds., *Food and Agriculture in Ethiopia: Progress and Policy Challenges*. University of Pennsylvania Press, Philadelphia, PA.

Conley, T.G., C.R. Udry. 2010. Learning about a New Technology: Pineapple in Ghana. *American Economic Review* 100: 35–69.

Croppenstedt, A., M. Demeke, M. Meschi. 2003. Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia. *Review of Development*

Economics 7: 58–70.

de Janvry, A., E. Sadoulet. 2002. World poverty and the role of agricultural technology: direct and indirect effects. *Journal of Development Studies* 38: 1-26.

Deininger, K., S. Jin. 2006. Tenure security and land-related investment: Evidence from Ethiopia. *European Economic Review* 50: 1245–1277.

Ersado, L., G. Amacher, J. Alwang. 2004. Productivity and land enhancing technologies in Northern Ethiopia: health, public investments, and sequential adoption. *American Journal of Agricultural Economics* 86: 321-331.

Evenson, R. E., D. Gollin. 2003. *Crop Variety Improvement and Its Effect on Productivity: The impact of international agricultural research*. CABI Publishing, Wallingford, UK.

Feleke, S., T. Zegeye. 2006. Adoption of improved maize varieties in Southern Ethiopia: Factors and strategy options. *Food Policy* 31: 442–457.

Fox, J.T., K. Kim, S. Ryan, P. Stephen, P. Bajari. 2012. The random coefficients logit model is identified. *Journal of Econometrics* 166: 204-212

Gebremedhin, B., S. Swinton. 2006. Determinants of farmer perceptions of the severity and yield impact of soil erosion in Northern Ethiopia. *Ethiopian Journal of Agricultural Economics* 6: 1-15

Jaleta, M., C. Yirga, M. Kassie, H. de Groote, B. Shiferaw. 2013. Knowledge, adoption and use intensity of improved maize technologies in Ethiopia. Invited paper presented at the 4th International Conference of the African Association of Agricultural Economists, September 22-25, 2013, Hammamet, Tunisia.

Langyingtuo, A.S., C. Mungoma. 2008. The effect of household wealth on the adoption of improved maize varieties in Zambia. *Food Policy* 33: 550-559.

Legese, G., A.S. Langyintuo, W. Mwangi, M. Jaleta. 2011. Determinants of adoption of improved drought tolerant maize varieties and their implication for household food security in drought prone areas. E*thiopian Journal of Agricultural Economics* 8: 105-132.

Leathers, H. D., M. Smale. 1991. A Bayesian approach to explaining sequential adoption of components of a technological package. *American Journal of Agricultural Economics* 73: 734-742.

Lin, J.Y. 1991. Education and Innovation Adoption in Agriculture: Evidence from

Hybrid Rice in China. *American Journal of Agricultural Economics* 73: 713-723.

Lunduka, R., M. Fisher, S. Snapp. 2012. Could farmer interest in a diversity of seed attributes explain adoption plateaus for modern maize varieties in Malawi? *Food Policy* 37: 504-510.

Munshi, K. 2004. Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution. *Journal of Development Economics* 73: 185-213.

Negatu, W., A. Parikh. 1999. The impact of perception and other factors on the adoption of agricultural technology in the Moret and Jiru Woreda (district) of Ethiopia. *Agricultural Economics* 21: 205-216.

Petrin, A., K. Train. 2010. A Control function approach to endogeneity in consumer choice models. *Journal of Marketing Research* 47: 3-13

Renkow, M., D. Byerlee. 2010. The impacts of CGIAR research: a review of recent evidence. *Food Policy* 35, 391–402.

Schneider, K., L. Anderson. 2010. Yield gap and productivity potential in Ethiopian agriculture: staple grains & pulses. EPAR Brief No. 98. Evans School Policy Analysis and Research. University of Washington, Seattle, WA.

Shiferaw, B., M. Smale, H.J. Braun, E. Duveiller, M. Reynolds, G. Muricho. 2013. Crops that feed the world 10. Past successes and future challenges to the role played by wheat in global food security. *Food Security* 5, 291-317.

Suri, T. 2011. Selection and comparative advantage in technology adoption. *Econometrica* 79, 159-209.

Train, K. 1986. *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*. The MIT Press. Cambridge, MA.

Train, K. 2003. *Discrete Choice Methods with Simulation*. Cambridge University Press, New York.

Tura, M., D. Aredo, W. Tsegaye, R. La Rovere, G. Tesfahun, W. Mwangi, G. Mwabu 2010. Adoption and continued use of improved maize seeds: Case study of Central Ethiopia. *African Journal of Agricultural Research*, 5(17): 2350-2358.

Useche, P., B.L. Barham, J.D. Foltz. 2009. Integrating technology traits and producer heterogeneity: a mixed-multinomial model of genetically modified corn adoption. *American Journal of Agricultural Economics* 91: 444-461.

Useche, P., B.L. Barham, J.D. Foltz. 2013. Trait-based adoption models using ex-ante and ex-post approaches. *American Journal of Agricultural Economics* 95: 332-338.

Wooldridge, J., 2007. What's New in Econometrics? Lecture 6: Control functions and related methods. NBER Summer Institute.
http://www.nber.org/WNE/Slides7-31-07/slides_6_controlfuncs.pdf

Zeng, D., J. Alwang, G.W. Norton, B. Shiferaw, M. Jaleta, C. Yirga. 2013. Ex-post impacts of improved maize varieties on poverty in rural Ethiopia. Diffusion and impact of improved varieties in Africa (DIIVA) - Objective 3 Report. Virginia Tech: Blacksburg, VA and CIMMYT: Nairobi, Kenya.

Table 4.1. Summary of Selected Characteristics[1, 2]

	Full sample (n = 1,072)	Included obs. (n = 960)	Excluded obs. (n = 112)
Total land holding (ha)	2.102 (1.593)	2.114 (1.641)	2.005 (1.539)
Maize area (ha)	1.621 (1.421)	1.580 (1.378)	1.972 (1.611)*
Altitude (meter)	1839 (294.0)	1836 (267.6)	1860 (338.7)
Season (long = 1; short = 0)	.940 (.174)	.939 (.193)	.953 (.151)
Distance to nearest main market (minute)	55.36 (49.92)	54.95 (50.03)	58.87 (48.32)
Distance to nearest seed dealer (minute)	48.08 (60.69)	47.56 (61.66)	52.52 (57.98)
Distance to nearest fertilizer dealer (minute)	29.99 (30.69)	29.44 (29.35)	34.67 (38.83)*
Household size	6.590 (2.355)	6.607 (2.327)	6.446 (2.546)
Total asset (thousand Ethiopia birrs, ETB[3])	17.98 (43.97)	18.31 (38.30)	15.14 (56.81)
Unmet credit need (yes = 1; no = 0)	.027 (.161)	.027 (.163)	.026 (.159)
Head gender (male = 1; female = 0)	.953 (.240)	.955 (.207)	.932 (.299)
Head marriage (married = 1; other = 0)	.947 (.237)	.949 (.197)	.928 (.299)
Head age	43.16 (12.48)	42.91 (12.40)	45.28 (12.95)
Head education (years)	2.933 (3.203)	2.961 (3.305)	2.692 (2.936)
Observed maize output price (ETB/kg)	2.991 (2.224)	2.967 (2.208)	3.196 (2.314)
Observed seed price (ETB/kg)	4.033 (3.579)	3.998 (3.506)	4.333 (3.952)
Observed fertilizer price (ETB/kg)	8.051 (6.277)	8.038 (5.983)	8.162 (7.154)
No. of observations in Tigray	19	19	0
No. of observations in Amhara	255	251	4
No. of observations in Oromia	654	556	98
No. of observations in SNNPR	144	144	0
Yield (kg/ha)[4]	2,859 (1,830)	2,886 (1,837)	2,625 (1,805)

[1] Sample means are reported, with standard deviations reported in parentheses.

[2] Pairwise *t*-tests between 960 included observations and 112 excluded observations are implemented. *, **, *** indicate the significance at 10%, 5% and 1% levels, respectively.

[3] The daily average exchange rate in 2010 is 1 US dollar = 14.38 Ethiopian birrs.

[4] Computed as plot-level average as a household may have multiple maize plots.

Table 4.2. Summary of Farmers' adoption behavior over time (n = 1,398)[1]

	Will adopt in the future	Will not adopt in the future
Adopted in 2009/10	761 (744)	94 (94)
Not adopted in 2009/10	416 (205)	127 (81)

[1] Number of farmers in each category are reported in parentheses; double counting of farmer numbers exists as each farmer may report perceptions of multiple IMVs.

Table 4.3. Summary of Farmers' perceptions of IMV traits (n = 1,398)[1]

	Original scale[2]	Binary scale[3]
Grain yield	4.295 (.863)	.851 (.356)
Drought tolerance	3.972 (1.187)	.667 (.499)
Water-logging tolerance	3.011 (.919)	.562 (.597)
Disease resistance	3.475 (1.402)	.544 (.498)
Pest resistance	3.330 (1.172)	.497 (.500)
Early maturity	4.056 (.925)	.764 (.424)
Storability	3.653 (1.144)	.583 (.493)
Grain size	3.475 (1.163)	.714 (.559)
Grain price	4.003 (.939)	.738 (.440)
Taste	4.180 (.840)	.796 (.403)
Overall varietal score	4.215 (.850)	.825 (.380)

[1] Standard deviations are reported in parentheses.

[2] The original scale indicates, from 1 to 5, that the trait of that improved maize variety very poor, poor, average, good and very good, as compared to local varieties.

[3] The binary scale indicates that the improved maize variety is either superior to local varieties (scored 1, if evaluated as very good or good) or of no significant advantage over that of local varieties (scored 0, if evaluated as average, poor and very poor).

Table 4.4. Identification of key IMV traits through IV regressions (dependent variable: overall varietal score; n = 1,398)[1]

	LPM	Probit	
		Coefficient	Marginal effect[2]
Grain yield	*.394 (.043)*	*.785 (.219)*	*.341 (.054)*
Drought tolerance	*.034 (.022)*	*.024 (.125)*	*.003 (.011)*
Water-logging tolerance	*.001 (.028)*	*.068 (.131)*	*.001 (.019)*
Disease resistance	*.051 (.021)*	*.154 (.056)*	*.042 (.014)*
Pest resistance	*.047 (.035)*	*.038 (.029)*	*.040 (.032)*
Early maturity	*-.019 (.022)*	*.036 (.055)*	*.002 (.025)*
Storability	*.049 (.020)*	*.137 (.051)*	*.041 (.020)*
Grain size	*.004 (.015)*	*.077 (.152)*	*.011 (.012)*
Grain price	*.078 (.022)*	*.386 (.121)*	*.045 (.024)*
Taste	*.193 (.024)*	*.306 (.107)*	*.217 (.041)*
Current adopter	.219 (.077)	.561 (.163)	.176 (.062)
Observed maize output price	.007 (.022)	.029 (.044)	.015 (.037)
Observed seed price	-.003 (.015)	.008 (.005)	.001 (.001)
Observed fertilizer price	-.005 (.009)	.002 (.018)	.000 (.003)
Total land holding	.002 (.002)	.014 (.005)	.004 (.002)
Season	-.054 (.070)	-.119 (.093)	-.080 (.087)
Distance to main market	.003 (.057)	.029 (.234)	.007 (.061)
Distance to seed dealer	-.044 (.198)	-.031 (.049)	.000 (.012)
Distance to fertilizer dealer	-.003 (.009)	.017 (.041)	.000 (.003)
Household size	-.013 (.007)	-.120 (.065)	-.013 (.006)
Total asset	.022 (.031)	.105 (.083)	.075 (.054)
Unmet credit need	.003 (.002)	-.056 (.038)	-.004 (.004)
Head gender	-.114 (.101)	-.066 (.094)	-.009 (.033)
Head marriage	-.014 (.107)	.192 (.237)	.033 (.125)
Head age	.005 (.038)	.018 (.021)	.004 (.007)
Head education	-.004 (.004)	-.082 (.088)	-.003 (.004)
Regional dummy: Amhara	.022 (.017)	.115 (.334)	.031 (.047)
Regional dummy: Oromia	-.027 (.033)	-.117 (.174)	-.048 (.031)
Regional dummy: SNNPR	.018 (.040)	.101 (.161)	.015 (.033)
CF: grain yield	.017 (.009)	.113 (.037)	.023 (.007)
CF: drought tolerance	.013 (.010)	.023 (.011)	.015 (.009)
CF: water-logging tolerance	-.003 (.005)	-.037 (.056)	.001 (.005)
CF: disease resistance	.005 (.001)	.016 (.003)	.008 (.003)
CF: pest resistance	.003 (.001)	.014 (.005)	.006 (.002)
CF: early maturity	-.012 (.026)	.006 (.027)	-.004 (.012)
CF: storability	.022 (.006)	.048 (.029)	.014 (.015)
CF: grain size	-.009 (.001)	.011 (.007)	.013 (.011)
CF: grain price	.011 (.002)	.003 (.013)	.002 (.006)

CF: taste	.009 (.004)	.077 (.034)	.015 (.004)
CF: current adopter	.042 (.009)	.085 (.028)	.039 (.015).
Constant	.054 (.390)	.198 (.163)	
F (*p*) / LR chi-square (*p*)	64.93 (.000)	341.8 (.000)	
Adjusted R^2 / Pseudo R^2	.274	.267	

[1] Standard errors are reported in parentheses. Perceptions of IMV traits are presented in italics.

[2] Probit marginal effects are computed using delta-method.

Table 4.5. Mixed logit estimation of binary adoption intention (n = 1,398)[1, 2]

	Coefficient	St. Dev.	Marginal effect[3]
Grain yield	*2.359 (.766)*	*1.577 (.063)*	*.434 (.157)*
Disease resistance	*.593 (.752)*	*.474 (.192)*	*.075 (.095)*
Storability	*-1.034 (.812)*	*.556 (.237)*	*-.266 (.252)*
Grain price	*.279 (.382)*	*.091 (.046)*	*.037 (.052)*
Taste	*1.509 (1.174)*	*1.116 (.353)*	*.144 (.185)*
Current adopter	.758 (.870)	.266 (.210)	.091 (.098)
Current adopter × Grain yield	*2.423 (.894)*		*.246 (.074)*
Current adopter × Disease resistance	*-.123 (.858)*		*.075 (.095)*
Current adopter × Storability	*.013 (.177)*		*-.039 (.111)*
Current adopter × Grain price	*.005 (.003)*		*.002 (.001)*
Current adopter × Taste	*-1.120 (.878)*		*-.149 (.121)*
Observed maize output price	.053 (.031)	.075 (.088)	.009 (.005)
Observed seed price	-.016 (.006)	.008 (.012)	-.004 (.001)
Observed fertilizer price	-.005 (.107)	.004 (.064)	.000 (.008)
Total land holding	.006 (.028)	.031 (.007)	.001 (.004)
Season	-.813 (.461)	.122 (.181)	-.036 (.019)
Distance to main market	.005 (.003)	.005 (.003)	.001 (.000)
Distance to seed dealer	-.014 (.002)	.027 (.013)	.002 (.000)
Distance to fertilizer dealer	.001 (.006)	.012 (.002)	.000 (.001)
Household size	-.111 (.095)	.205 (.124)	-.014 (.012)
Total asset	.074 (.087)	.393 (.168)	.009 (.007)
Unmet credit need	-.077 (.026)	.059 (.014)	-.012 (.005)
Head gender	.719 (1.775)	.044 (.130)	.072 (.133)
Head marriage	.024 (1.683)	.013 (.007)	.003 (.218)
Head age	.001 (.022)	.019 (.009)	.000 (.003)
Head education	.130 (.058)	.174 (.101)	.017 (.007)
Regional dummy: Amhara	-.342 (.576)		-.048 (.088)
Regional dummy: Oromia	1.088 (.434)		.157 (.069)
Regional dummy: SNNPR	.034 (.131)		.004 (.022)
CF: grain yield	.011 (.004)	.113 (.306)	.001 (.000)
CF: disease resistance	.003 (.002)	.045 (.037)	.000 (.005)
CF: storability	.016 (.012)	.019 (.017)	.003 (.002)
CF: grain price	.005 (.002)	.003 (.006)	.000 (.000)
CF: taste	.027 (.015)	.067 (.099)	.002 (.002)
CF: current adopter	.135 (.046)	.115 (.076)	.017 (.009)
Constant	-6.701 (3.347)	3.341 (1.635)	

[1] Standard errors are reported in parentheses. Bootstrapping of 100 times is employed.

[2] Log likelihood: -128.77. Wald chi-square statistic: 166.85 (p = 0.000).

[3] Marginal effects of interactive terms are computed following Ai and Norton (2003). Other marginal effects are computed using delta-method.

Table 4.6. Maize yield by previous adoption status and perception (n = 1,398)[1, 2]

Category	Actual yield (kg/ha)	Within-village yield ratio
Current adopters with yield perception of 1	3,355 (1,913)	1.036*** (.095)
Current adopters with yield perception of 0	3,274 (1,885)	.861*** (.071)
Current non-adopters with yield perception of 1	2,290 (1,638)	.967 (.066)
Current non-adopters with yield perception of 0	2,382 (1,707)	1.012 (.049)

[1] Plot-level yield is employed in the computation as a household may have multiple plots with varying yield levels. Standard deviations are reported in parentheses.

[2] Pairwise *t*-tests are performed for both actual yield and within-village yield ratio between farmers of the same current adoption behavior but different yield perceptions. *, **, *** indicate the significance at 10%, 5% and 1% levels, respectively.