**Agricultural Technology Adoption and Child Nutrition:**

**Improved Maize Varieties in Rural Ethiopia**

Di Zeng (Virginia Tech)
Jeffrey Alwang (Virginia Tech)
George W. Norton (Virginia Tech)
Bekele Shiferaw (Partnership for Economic Policy)
Moti Jaleta (International Maize and Wheat Improvement Center)
Chilot Yirga (Ethiopian Institute of Agricultural Research)

*Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.*

**Abstract:** Adoption of agricultural technology can lead to multiple benefits to farm households, including increased productivity, incomes and food consumption. However, specific causal linkages between agricultural technology adoption and child nutrition outcomes are rarely explored in the literature. This paper helps bridge this gap through an impact assessment of the adoption of improved maize varieties on child nutrition outcomes using a recent household survey 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 poorest nutritional outcomes. By combining a decomposition procedure with system of equations estimation, 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.

**Key words:** child nutrition, impact, improved maize varieties, Ethiopia

## 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.

**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.

**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 $\theta_{ij}$, the resource allocation decision within the household, can be a function of both household and child characteristics. If $\phi$ 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) $$p_R R_i + p_C C_i = [p_M(Q_i^M - M_i) - p_X X_i^M] + [p_F(Q_i^F - F_i) - p_X X_i^F] + I_i$$

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

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 $\varepsilon_{ij}^{N}$ :

(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 $\varepsilon_{ij}^{t}$, 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 $\alpha_3$ 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 $\nu_{ij}$ 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:

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

**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.

**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

[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.

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. 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

[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 ($p = 0.119$).

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.

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

[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.

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

[5] 1 kert equals 0.25 hectare.

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 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 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

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

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 and WAZ models, the consumption of own-produced maize, and total expenditures on

[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 provided in the Appendix as the system of equations is huge, and most coefficient estimates are not of our direct interest.

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 $\gamma_1^M$ in Table 3, after controlling for household size and other characteristics. Adoption is also associated with increases in household expenditures on non-food items ( $\gamma_1^C$ ). But a one kert increase in IMV acreage reduces total household food expenditure by 228 Ethiopian birrs annually ( $\gamma_1^R$ , 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 ( $\gamma_1^F$ ), 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 ( $\gamma_1^N$ ) and other own-produced foods ( $\gamma_2^N$ ) are significant. Contributions through purchased foods ( $\gamma_3^N$ ) and purchased non-food items ( $\gamma_4^N$ ) are insignificant, although both have positive signs as 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, ($\gamma_1^N$) and the effect of own-produced maize consumption on child nutrition ($\gamma_1^M$) 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.

## 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 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 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 GMM 3SLS Estimation of Partial Effects (n = 1,216)[1]**

| | HAZ | WAZ |
|---|---|---|
| $\gamma_1^M$ | 2.94*** (.753) | 2.94*** (.753) |
| $\gamma_1^F$ | -.337 (.354) | -.337 (.354) |
| $\gamma_1^R$ | -2.28*** (.786) | -2.28*** (.786) |
| $\gamma_1^C$ | .731** (.341) | .731** (.341) |
| $\gamma_1^N$ | .063*** (.022) | .033** (.015) |
| $\gamma_2^N$ | .023** (.008) | .009*** (.003) |
| $\gamma_3^N$ | .007 (.012) | .003 (.007) |
| $\gamma_4^N$ | .001 (.004) | .006 (.005) |

[1] Standard errors reported in parentheses. ***, **, * indicate 1%, 5% and 10% significance, respectively. Full estimation results are presented in the Appendix.

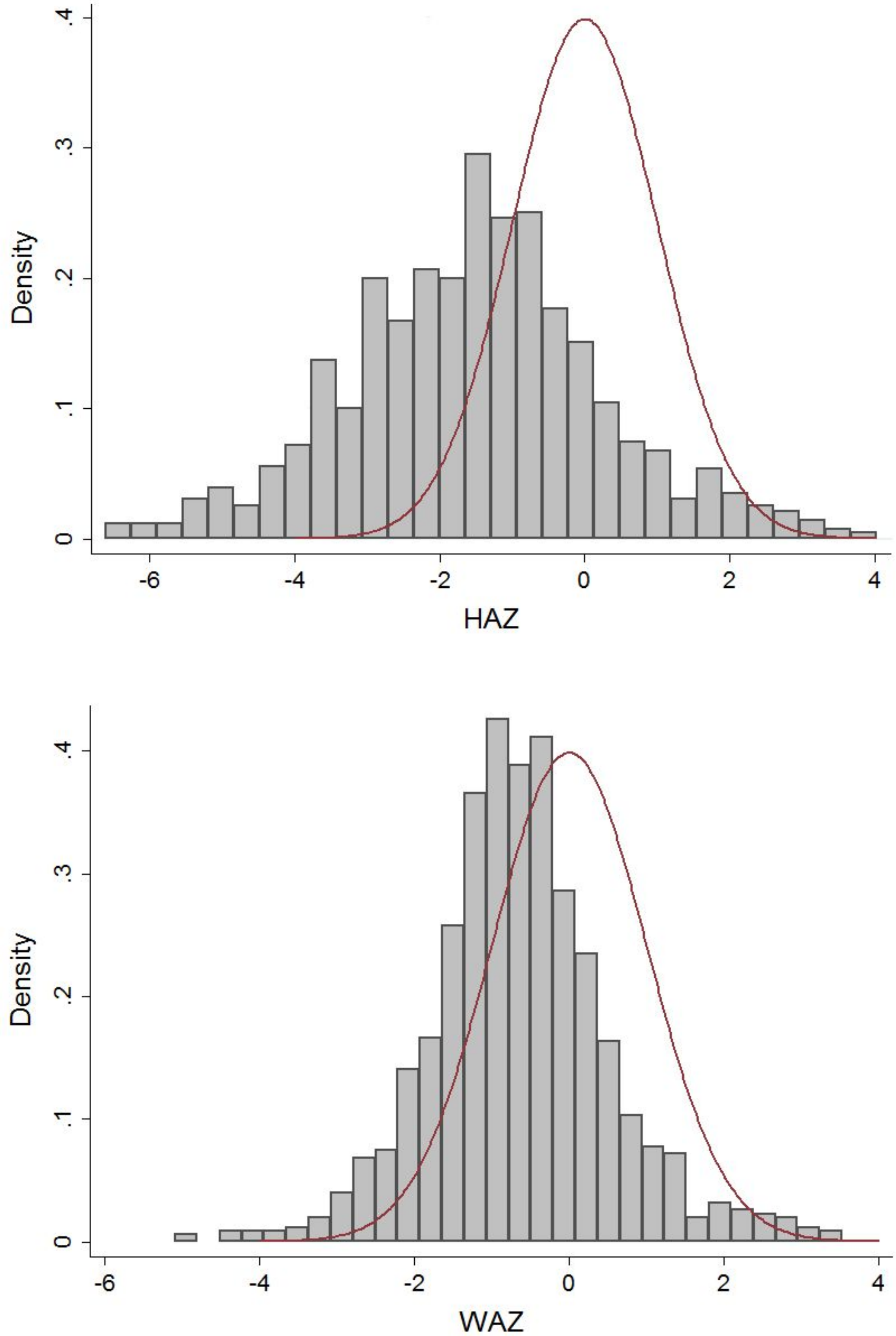


**Figure 1 HAZ and WAZ of surveyed children (n = 1,216)**

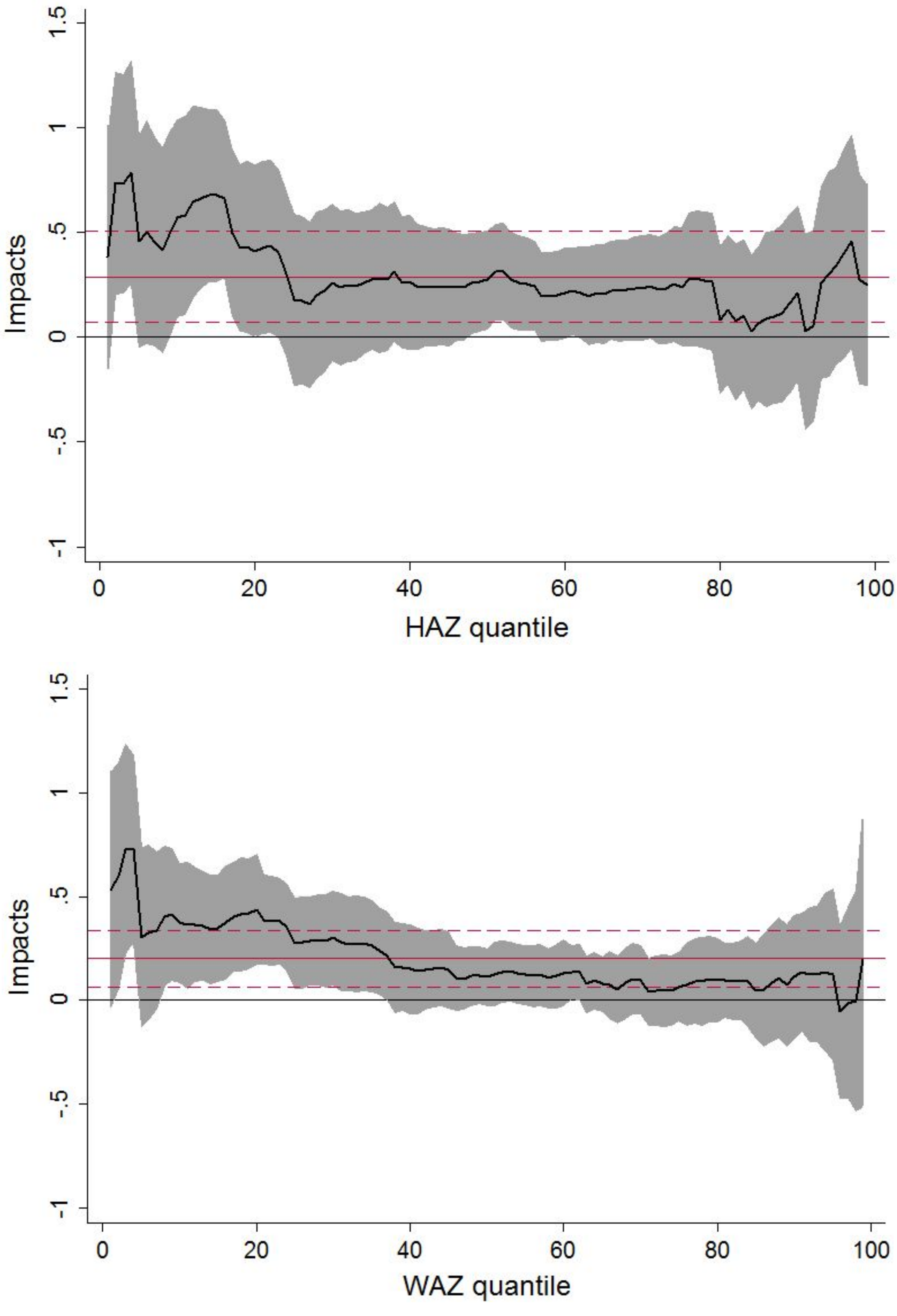


**Figure 2 Quantile impacts on HAZ and WAZ (n = 1,216)[1]**

[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.

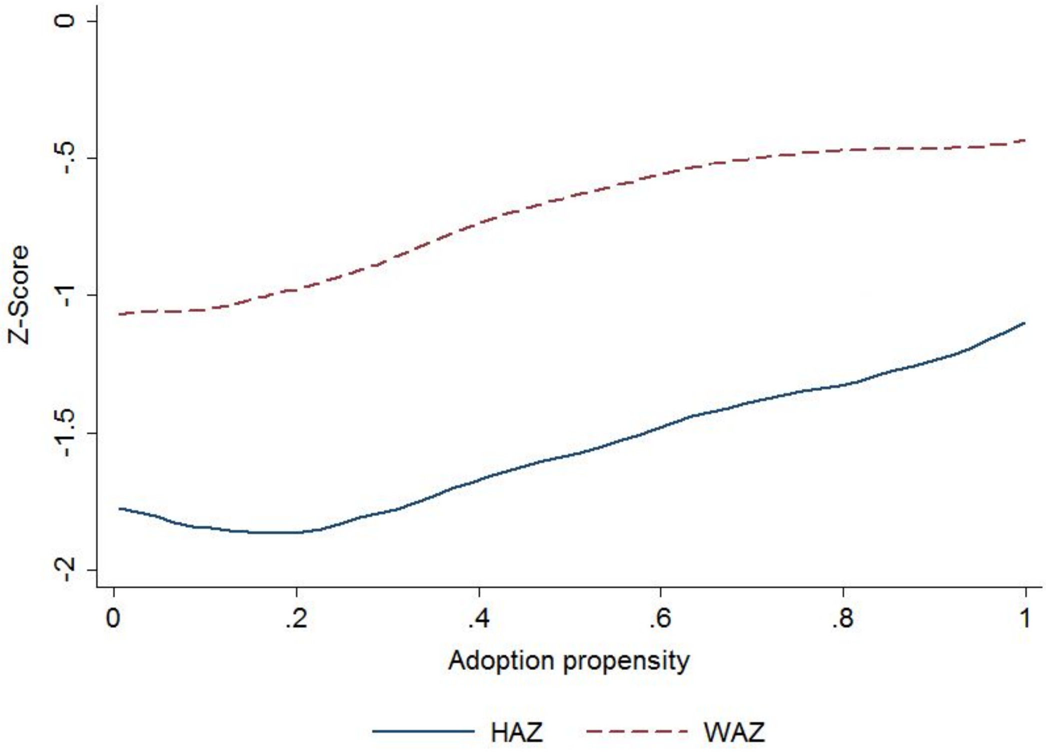


**Figure 3 Child nutrition outcomes by adoption propensity**

## Appendix: Full Results of System of Equations Estimation

Table A1 and A2 presents the GMM 3SLS estimates of the system of equations (12.1) - (12.7), respectively.

**Table A1 GMM 3SLS Estimation of System of Equations (12.1) - (12.7): HAZ Model[1, 2]**

| | (12.1) | (12.2) | (12.3) | (12.4) | (12.5) | (12.6) | (12.7) |
|---|---|---|---|---|---|---|---|
| Years known | .009 (.002) | .006 (.002) | | | | | |
| Supply disruption | -.003 (.001) | -.007 (.002) | | | | | |
| Distance to seed dealer | -.006 (.001) | -.003 (.001) | | | | | |
| *IMV area* | | | *2.94 (.753)* | *-.337 (.354)* | *-2.28 (.786)* | *.731 (341)* | |
| *Own-produced maize* | | | | | | | *.063 (.022)* |
| *Other produced foods* | | | | | | | *.023 (.008)* |
| *Purchased foods* | | | | | | | *.007 (.012)* |
| *Purchased non-food* | | | | | | | *.001 (.003)* |
| Total land | .189 (.046) | .251 (.074) | .122 (.065) | 1.08 (.671) | .156 (.107) | .022 (.012) | |
| Total maize area | | | .242 (.202) | -.877 (.359) | -.233 (.334) | -.041 (.038) | |
| Child gender | | | .197 (.148) | .043 (.098) | -.088 (.117) | .004 (.011) | -.273 (.294) |
| Child age | | | .015 (.017) | .013 (.005) | -.002 (.001) | .002 (.013) | -.054 (.022) |
| Child age square | | | .000 (.001) | .000 (.001) | -.000 (.000) | -.000 (.000) | .002 (.001) |
| Siblings | | | .202 (.105) | .267 (.090) | .156 (.085) | .014 (.009) | -.229 (.067) |
| Total off-farm income | | | .103 (.057) | .095 (.257) | .677 (.231) | .163 (.061) | .018 (.010) |
| Adoption history | | | .211 (.403) | -.037 (.026) | .003 (.004) | .044 (.012) | .123 (.055) |
| Household size | -.007 (.034) | .024 (.035) | .209 (.045) | .176 (.314) | 4.33 (1.08) | -.030 (.004) | -.241 (.313) |
| Head gender | .122 (.065) | .447 (.373) | .680 (.296) | .337 (.172) | .368 (.193) | -.033 (.056) | .263 (.384) |
| Head age | -.007 (.007) | -.019 (.006) | ..020 (.014) | .485 (.063) | .115 (.073) | .001 (.001) | -.019 (.016) |
| Head education | .096 (.022) | .131 (.021) | .004 (.004) | -.03 (.042) | -.007 (.006) | -.006 (.005) | .047 (.017) |
| Head marriage | .317 (.490) | -.563 (.487) | -.297 (.645) | 1.17 (.546) | -.730 (.612) | -.022 (.007) | -.149 (.396) |
| Total assets | .007 (.003) | .005 (.002) | .003 (.001) | .024 (.059) | .019 (.007) | .295 (1.45) | .004 (.002) |
| Private toilet | .241 (.175) | -.171 (.174) | -..018 (.242) | .199 (.078) | .282 (.204) | .055 (.023) | .204 (.143) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Piped water | .104 (.142) | .525 (.161) | .051 (.225) | .030(.004) | .635 (.264) | .079 (.030) | .004 (.122) |
| Maize price | | | -.189 (.091) | .141 (.036) | -061 (.094) | .000(.004) | |
| Teff price | | | .084 (.114) | -.083 (.080) | .046 (.014) | .002 (.014) | |
| Wheat price | | | .446 (.088) | -.024 (.011) | .029 (.073) | -.012 (.007) | |
| Barley price | | | .281 (.069) | .051 (.184) | .210 (.071) | .005 (.007) | |
| Soap price | | | .262 (.227) | .078 (.023) | .598 (.342) | .050 (.038) | |
| Maize seed price | -.230 (.049) | -.117 (.048) | -.259 (.134) | .064 (.011) | .096 (.101) | .000 (.009) | |
| Fertilizer price | -.098 (.100) | -.353 (.097) | -.277 (.365) | -.245 (.351) | -.286 (.191) | .006 (.002) | |
| Region: Amhara | .195 (.483) | -.442 (.478) | 2.72 (1.09) | 1.36 (.753) | 2.52 (1.39) | .079 (.153) | .257 (.480) |
| Region: Oromia | .168 (.472) | .299 (.335) | 2.53 (.948) | 2.82 (1.15) | 2.67(1.04) | .198 (.114) | .189 (.403) |
| Region: SNNPR | -.123 (.527) | -.025 (.519) | 2.45 (1.16) | .361 (.160) | 2.36 (1.51) | .097 (.166) | -.035 (.146) |
| Constant | .197 (.036) | 4.02 (.915) | 3.35 (2.13) | 33.19 (18.22) | 86.23 (32.7) | 98.04 (17.21) | -6.99 (1.79) |

[1] Standard errors are presented in parentheses.

[2] Partial effects of our interest are presented in italics, and summarized in Table 3.

Table A2 GMM 3SLS Estimation of System of Equations (12.1) - (12.7): WAZ Model[1, 2]

| | (12.1) | (12.2) | (12.3) | (12.4) | (12.5) | (12.6) | (12.7) |
|---|---|---|---|---|---|---|---|
| Years known | .009 (.002) | .006 (.002) | | | | | |
| Supply disruption | -.003 (.001) | -.007 (.002) | | | | | |
| Distance to seed dealer | -.006 (.001) | -.003 (.001) | | | | | |
| *IMV area* | | | *2.94 (.753)* | *-.337 (.354)* | *-2.28 (.786)* | *.731 (341)* | |
| *Own-produced maize* | | | | | | | *.033 (.015)* |
| *Other produced foods* | | | | | | | *.009 (.003)* |
| *Purchased foods* | | | | | | | *.003 (.007)* |
| *Purchased non-food* | | | | | | | *.006 (.005)* |
| Total land | .189 (.046) | .251 (.074) | .122 (.065) | 1.08 (.671) | .156 (.107) | .022 (.012) | |
| Total maize area | | | .242 (.202) | -.877 (.359) | -.233 (.334) | -.041 (.038) | |
| Child gender | | | .197 (.148) | .043 (.098) | -.088 (.117) | .004 (.011) | .051 (.077) |
| Child age | | | .015 (.017) | .013 (.005) | -.002 (.001) | .002 (.013) | -.022 (.010) |
| Child age square | | | .000 (.001) | .000 (.001) | -.000 (.000) | -.000 (.000) | .000 (.000) |
| Siblings | | | .202 (.105) | .267 (.090) | .156 (.085) | .014 (.009) | -.104 (.037) |
| Total off-farm income | | | .103 (.057) | .095 (.257) | .677 (.231) | .163 (.061) | .001 (.001) |
| Adoption history | | | .211 (.403) | -.037 (.026) | .003 (.004) | .044 (.012) | .141 (.075) |
| Household size | -.007 (.034) | .024 (.035) | .209 (.045) | .176 (.314) | 4.33 (1.08) | -.030 (.004) | .013 (.026) |
| Head gender | .122 (.065) | .447 (.373) | .680 (.296) | .337 (.172) | .368 (.193) | -.033 (.056) | .263 (.384) |
| Head age | -.007 (.007) | -.019 (.006) | ..020 (.014) | .485 (.063) | .115 (.073) | .001 (.001) | .009 (.027) |
| Head education | .096 (.022) | .131 (.021) | .004 (.004) | -.03 (.042) | -.007 (.006) | -.006 (.005) | .035 (.018) |
| Head marriage | .317 (.490) | -.563 (.487) | -.297 (.645) | 1.17 (.546) | -.730 (.612) | -.022 (.007) | .126 (.174) |
| Total assets | .007 (.003) | .005 (.002) | .003 (.001) | .024 (.059) | .019 (.007) | .295 (1.45) | .001 (.001) |
| Private toilet | .241 (.175) | -.171 (.174) | -..018 (.242) | .199 (.078) | .282 (.204) | .055 (.023) | .098 (.073) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Piped water | .104 (.142) | .525 (.161) | .051 (.225) | .030(.004) | .635 (.264) | .079 (.030) | .113 (.102) |
| Maize price | | | -.189 (.091) | .141 (.036) | -061 (.094) | .000(.004) | |
| Teff price | | | .084 (.114) | -.083 (.080) | .046 (.014) | .002 (.014) | |
| Wheat price | | | .446 (.088) | -.024 (.011) | .029 (.073) | -.012 (.007) | |
| Barley price | | | .281 (.069) | .051 (.184) | .210 (.071) | .005 (.007) | |
| Soap price | | | .262 (.227) | .078 (.023) | .598 (.342) | .050 (.038) | |
| Maize seed price | -.230 (.049) | -.117 (.048) | -.259 (.134) | .064 (.011) | .096 (.101) | .000 (.009) | |
| Fertilizer price | -.098 (.100) | -.353 (.097) | -.277 (.365) | -.245 (.351) | -.286 (.191) | .006 (.002) | |
| Region: Amhara | .195 (.483) | -.442 (.478) | 2.72 (1.09) | 1.36 (.753) | 2.52 (1.39) | .079 (.153) | .411 (.367) |
| Region: Oromia | .168 (.472) | .299 (.335) | 2.53 (.948) | 2.82 (1.15) | 2.67(1.04) | .198 (.114) | .272 (.219) |
| Region: SNNPR | -.123 (.527) | -.025 (.519) | 2.45 (1.16) | .361 (.160) | 2.36 (1.51) | .097 (.166) | .344 (.672) |
| Constant | .197 (.036) | 4.02 (.915) | 3.35 (2.13) | 33.19 (18.22) | 86.23 (32.7) | 98.04 (17.21) | -3.89 (1.63) |

[1] Standard errors are presented in parentheses.

[2] Partial effects of our interest are presented in italics, and summarized in Table 3.