JAE Journal of Agricultural Economics

Journal of Agricultural Economics, Vol. 69, No. 1, 2018, 76–95
doi: 10.1111/1477-9552.12221

Measuring Farm and Market Level Economic Impacts of Improved Maize Production Technologies in Ethiopia: Evidence from Panel Data

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(Original submitted September 2016, revision received February 2017, accepted April 2017.)

Abstract

While it is often recognised that agricultural technology adoption decisions are intertwined and best characterised by multivariate models, typical approaches to examining adoption and impacts of agricultural technology have focused on single technology adoption choice and ignored interdependence among technologies. We examine farm- and market-level impacts of multiple technology adoption choices using comprehensive household survey data collected in 2010/11 and 2012/13 in Ethiopia. Economic surplus analysis combined with panel data switching endogenous regression models are used to compute the supply shift parameter (K-shift parameter), while at the same time controlling for the endogeneity inherent in agricultural technology adoption among farmers. We find that our improved technology set choices have significant impacts on farm-level maize yield and maize production costs, where the greatest effect appears to be generated when various

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technologies are combined. The change in maize yield and production costs results in an average 26.4% cost reduction per kilogram of maize output (the K-shift parameter). This increases the producer and consumer surpluses by US$ 140 and US$ 105 million per annum, respectively. These changes in economic surplus help to reduce the number of poor people by an estimated 788 thousand per year. We conclude that deliberate extension efforts and other policies that encourage integration of technologies are important for maize technologies to yield their full potential at both farm and market levels.

Keywords: *Economic surplus*; *ethiopia*; *maize*; *multiple technology adoption*; *panel data*; *poverty*.

JEL classifications: *C23, I32, O33, Q16*.

1. Introduction

While it is recognised that agricultural technology adoption decisions among smallholder farmers are best characterised by multivariate models (e.g. Dorfman, 1996; Wu and Babcock, 1998; Kassie *et al*., 2013; Teklewold *et al*., 2013), the most common approaches to examining adoption and impacts of agricultural technology have presented the decision to adopt as a single technology adoption choice. Yet the impacts of any agricultural technology frequently arise from the judicious application of multiple interrelated practices at the farm level. A single technology cannot reach its full potential unless interrelated technologies and complementary practices are also implemented. In fact, it is arguable that the continued persistence of low yields among smallholder farmers is partly and sometimes largely due to their failure to implement new crop varieties with complementary production practices (Kassie *et al*., 2015a). The focus on modelling adoption as a process involving the joint application of multiple practices is therefore important to properly inform agricultural policies for research and effective extension packages for farmer education to achieve maximum impact from these technologies.

Since new agricultural technologies, whether better crop varieties or superior agronomic management practices, can have far reaching impacts (De Janvry and Sadoulet, 2002), it is also important to identify both the direct benefits of technology adoption at the farm level and the indirect benefits that accrue on other economic agents beyond the farm. The former includes private economic impacts and the latter includes market-level economic impacts. There is a considerable body of literature that has examined the impact of single agricultural technology in terms of direct and indirect impacts (e.g. Lence and Dermot, 2005; Mendola, 2007; Moyo *et al*., 2007; Krishna and Qaim, 2008; Alene *et al*., 2009; Kassie *et al*., 2011; Zeng *et al*., 2015). However, the literature analysing technology combinations and their direct and indirect effects beyond the household level is sparse. Relatively recent papers such as Moyo *et al*. (2007), Alene *et al*. (2009) and Zeng *et al*. (2015) consider the technology-induced price effect on poverty reduction but exclusively examine improved maize and groundnut varieties in eastern Uganda and West Africa and Ethiopia, respectively. Even then, there is limited consideration of other indirect effects (such as benefits to poor non-farm household consumers and employment creation along the value chain) with possible implications for poverty.

The contribution of this paper is threefold. First, we examine the empirical evidence on economic impacts of maize production technologies at both farm and market levels. Second, we estimate the implied poverty impacts of these maize technologies beyond the farm level. Third, we examine these impacts based on combinations of maize production technologies that affect farm- and, by extension, market-level impacts.

The combinations of technologies/practices considered are: improved maize seeds, chemical fertilisers, and legume diversification (maize–legume intercropping or rotation). The basic framework of analysis relies on the combination of economic surplus analysis with panel econometric methods to control for the endogenous adoption decisions. The econometric methods are used to estimate a supply shift parameter (K-shift parameter) through estimating changes in farm-level maize yields and costs of production due to adoption. These parameters are then incorporated in the economic surplus analysis to compute the total change in economic surplus gains. Finally, the economic surplus benefits are used to estimate the poverty reduction effects of adoption.

In the recent past, maize has emerged as a leading cereal crop in Ethiopia, second only to *teff* in the production and subsistence profiles of many households. It has been reported that more households now grow maize than any other cereal in Ethiopia (Abate *et al.*, 2015). In a study of market participation of maize growing households in Ethiopia, Marenya *et al.* (2017) found that maize accounts for up to 61% of all crop sales among male-headed households and 58% among households led by women; implying that maize is a major economic crop with important implications for household welfare. The importance of maize is confirmed by the focus of stakeholders – particularly the national research system, in conjunction with international research organisations and donor agencies – who have invested considerably in maize research in Ethiopia, with the result that more than 40 maize varieties adapted to diverse agro-ecologies have been released in the country (Abate *et al.*, 2015).

The emerging research evidence also clearly points to the need to compliment the release of varieties with better agronomy and resource management practices to achieve higher yield, food security, income and minimise risks (e.g. Di Falco and Veronesi, 2013, 2014; Teklewold *et al.*, 2013; Kassie *et al.*, 2015a,b; Manda *et al.*, 2016).

The rest of the paper is organised as follows. The next section describes the methodology used to analyse adoption and impacts of adoption. The third section describes the study area, data and provides summary statistics. Section 4 presents our estimation results. Section 5 concludes and draws policy implications.

2. Conceptual and Empirical Framework

2.1. Estimating impacts of adoption on farm-level yield and production costs

Evaluating the impacts of technology adoption requires controlling for potential selection bias and unobserved heterogeneity. If the selection process is based on time constant unobserved heterogeneity, a panel estimator solves the problem without an instrumental variable (Wooldridge, 2002). However, the selection process might be generated by time-varying unobserved heterogeneity that affects the outcomes (Wooldridge, 2002; Dustmann and Rochina-Barrachina, 2007). In this case, the availability of panel data alone might be inadequate to estimate the effects of technology set choices on outcomes of interest. To circumvent this problem, we combine a panel data estimator with an endogenous switching regression (ESR) model that enables us to capture time-varying unobserved heterogeneity. The ESR model also allows the technology set choices (treatment variables) to interact with observable variables and unobserved heterogeneity. This means that the effect of technology choice is not limited to the intercept of the outcome equations (as assumed by, for example, Zeng *et al*., 2015), but can also have a slope effect.[2] The ESR allows interaction by estimating separate regressions for adopters and non-adopters. The other advantage of the ESR over other methods such as propensity score matching is that the ESR enables the construction of a counterfactual based on returns to characteristics of adopters and non-adopters. The means of variables/characteristics could be the same for both groups but they may differ in terms of their returns (coefficient estimates) which have implications on adoption and productivity. For example the mean farm size could be equal but the returns to that land could differ substantially based on differential quality (e.g. one of them could be on flatter, less eroded land). Nevertheless, the ESR model remains somewhat limited by the joint normality assumption for both adoption and outcome equations.

We follow the Wooldridge (2002) approach for estimating unbalanced panel data where we estimate pooled OLS and pooled selection models using the Mundlak (1978) device. The fixed effects estimator does not provide consistent estimates in the presence of unbalanced data (Wooldridge, 2002). To implement the Mundlak approach, we include the means of all time-varying covariates in the adoption and outcome equations. The Mundlak device combines the fixed-effects and the random-effects estimation approaches. By including the vector of time-averaged variables, we control for time-constant unobserved heterogeneity, as with fixed effects, while avoiding the problem of incidental parameters in nonlinear models such as the multinomial logit model.

The estimation of multinomial switching endogenous regression framework involves a two-step estimation procedure. In the first step, a multinomial logit (MNL) model accounting for unobserved individual heterogeneity is estimated to generate inverse Mills ratios (selection correction terms).[3] In the second step, the outcome equations are estimated using OLS including the inverse Mills ratios as an additional regressor to capture selection bias due to time varying unobserved heterogeneity. Previous empirical studies have evaluated impact using an endogenous switching regression include Di Falco *et al*. (2011), Teklewold *et al*. (2013), Abdulai and Huffman (2014), Di Falco and Veronesi (2013) and Kassie *et al*. (2015a,b).

The adoption of three technologies/practices (improved maize seeds, chemical fertiliser and legume diversification) involves eight technology choice sets (including an 'empty' set where none of the technologies is adopted either singly or in combination) (Table 1). That means eight adoption equations were estimated using the MNL model. We base our analysis on the latent variable concept, where we assume that at

[2]Using Chow test statistics, we accept the alternative hypothesis in both yield and cost outcome equations that technology set also has a slope effect in addition to an intercept effect (see Table S1(A) in the online Appendix).

[3]Although the multinomial logit model depends on the assumption of Independence of Irrelevant Alternatives (IIA), it has been shown that the model is relatively robust in many cases in which this assumption is implausible (McFadden, 1980; Bourguignon *et al*., 2007).

Table 1
Adoption of technology set choices (%)

Technology set	D_1	D_0	F_1	F_0	V_1	V_0	2010	2013
$F_0V_0D_0$		√		√		√	29.89	23.29
$F_1V_0D_0$			√				12.66	10.56
$F_0V_1D_0$					√		9.18	7.63
$F_0V_0D_1$	√						2.4	3.79
$F_1V_1D_0$			√		√		36.67	41.59
$F_1V_0D_1$	√		√				1.8	1.99
$F_0V_1D_1$	√				√		1.15	1.18
$F_1V_1D_1$	√		√		√		6.26	9.97

Note: F, V and D refers to fertiliser, improved maize varieties and legume diversification; subscript '0' denotes non-adoption while '1' denotes adoption. The number of plot observations are 4,555 and 3,914 during 2010/11 and 2012/13, respectively.

each time period a farm household chooses a technology set that maximises expected utility. Let a farm household's utility of choosing a technology set j (j = 0, 1, 2, …, 7, and 'j = 0 'denoting that none of the practices was adopted, while the remaining technology sets (j = 1, …, 7) contain at least one technology) be represented by U_{jt}. A farm household chooses a technology set j if and only if its utility U_{jt} outweighs the utility (U_{kt}) that could be obtained from other technology sets i.e., $U_{jt} > U_{kt}$, $j \neq k$.

Following the literature on adoption behaviour and impact in developing countries (e.g. Marenya and Barrett, 2007; Di Falco *et al.*, 2011; Di Falco and Veronesi, 2013; Kassie *et al.*, 2013, 2015a,b,c; Teklewold *et al.*, 2013; Abdulai and Huffman, 2014), we specify the utility of adoption as a function of exogenous variables including household-, plot- and village-level variables. The probability that a farm household selects technology set j on a plot at time t conditional on X_{it} can be represented as:

$$\mathrm{Prob}(j|X_{it}, H_i) = \frac{\exp\left(\alpha_j + X_{it}\beta_j + H_i\right)}{\sum_{k=1}^{J}\exp(\alpha_k + X_{it}\beta_k + H_i)}, j = 0, 2, 3, \ldots, 7 \qquad (1)$$

where i indexes individual farmer, j indexes technology set and t indexes time period. The parameter α_j represents the specific constant term of technology set j; X_{it} is a matrix of observable household, plot and village characteristics and a time period dummy that affects the probability of adoption; H_i denotes time constant unobserved heterogeneity term and βj are unknown parameters to be estimated. As discussed above, the unobserved heterogeneity (H_i) will be replaced by means of the time-varying explanatory variable ($\bar{X}_i$), following Mundlak's approach. Equation (1) is estimated using a MNL model based on household- and plot-level panel data of Ethiopian maize farmers.

In the second stage of ESR, the maize yield (Q) and cost (C) functions are estimated for adopters and non-adopters separately controlling for the endogenous nature of technology adoption decisions. The eight plot-level maize yield and cost equations are specified as follows:

$$\begin{cases} \text{Regime0}: Q_{it0} = Z^q_{it0}\beta^q_0 + \hat{\lambda}_{it0}\sigma^q_0 + (\hat{\lambda}^q_{it0}T)\psi^q_0 + H^q_{i0} + \in^q_{it0} & \text{if } j = 0 \\ \vdots & \\ \text{RegimeJ}: Q_{itJ} = Z^q_{itJ}\beta^q_J + \hat{\lambda}_{itJ}\sigma^q_J + (\hat{\lambda}^q_{itJ}T)\psi^q_J + H^q_{iJ} + \in^q_{itJ} & \text{if } j = J, 1, \ldots, 7 \end{cases} \quad (2)$$

$$\begin{cases} \text{Regime 0}: C_{it0} = Z^c_{it0}\beta^c_0 + \hat{\lambda}_{it0}\sigma^c_0 + (\hat{\lambda}^c_{it0}T)\psi^c_0 + H^c_{i0} + \in^c_{it0} & \text{if } j = 0 \\ \vdots & \\ \text{Regime J}: C_{itJ} = Z^c_{itJ}\beta^c_J + \hat{\lambda}_{itJ}\sigma^c_J + (\hat{\lambda}^c_{itJ}T)\psi^c_J + H^c_{iJ} + \in^c_{itJ} & \text{if } j = J, 1, \ldots, 7 \end{cases} \quad (3)$$

where $j = 0$ denotes that neither of the technologies nor their combinations were adopted and $j = 1, \ldots 7$ represents adoption of either technology or their combinations; Q_{itj} and Q_{it0} are, respectively, maize yield per hectare (ha) of the ith household on a plot at time t with and without adoption of technology set j; Z_{it} is a set of observable household, plot- and village-level characteristics, including a time period dummy (T), that influence maize yield and production costs at time t; β and ψ are parameters to be estimated; H_i is time invariant unobservable household heterogeneity; $\hat{\lambda}$ are inverse Mills ratios derived from equation (1) to capture time-varying individual effects; σ is the covariance between the error terms of adoption and outcome equations; C_{itJ} and C_{it0} are, respectively, per hectare cost of maize production of the ith household on a plot at time t with and without a technology set j, and consist of labour (family and hired), fertiliser, seed (own and bought), chemical, manure, oxen and tractor costs.[4] As in the choice model, the time invariant unobserved variable (H) is parameterised by the mean values of time-varying explanatory variables ($\bar{Z}_i$). The interaction of $\hat{\lambda}$ and time period dummy (T) is based on Wooldridge (2002) for estimation of unbalanced panel data models.

2.1.1. Expected actual and counterfactual outcomes

To assess the effect of technology set choice on maize yield and cost of production, the counterfactual outcomes should be estimated. Equations (2) were used to generate the expected actual (observed) and counterfactual of maize yield for a farm household that adopted technology set j. The actual expected outcomes that are observed in the data are computed as:

$$E(Q_{itJ}/j = J) = Z^q_{itJ}\beta^q_J + \hat{\lambda}_{itJ}\sigma^q_J + (\hat{\lambda}^q_{itJ}T)\psi^q_J + \bar{Z}^q_{iJ}\varphi^q_J \qquad j = 1, 2, 3\ldots, 7 \quad (4)$$

On the other hand, the counterfactual expected value of maize yield on a plot with a technology set j that contains one or more improved technologies is given as follows:

$$E(Q_{it0}/j = J) = Z^q_{itJ}\beta^q_o + \hat{\lambda}_{itj}\sigma^q_0 + (\hat{\lambda}^q_{itJ}T)\psi^q_0 + \bar{Z}^q_{iJ}\varphi^q_0 \qquad j = 1, 2, 3, \ldots, 7 \quad (5)$$

where the parameters β^q_o, φ^q_0 and σ^q_0 are coefficients obtained from estimation of maize yield without a technology set ($j = 0$) and other variables are as defined above.

[4]Since most of the surveyed farm households rely on family labour, we imputed an opportunity cost of labour from the production function following Jacoby (1993).

Equation (5) is defined as the maize yield of technology set j (j = 1,2,3, ... 7) adopters which would have been obtained if the returns (coefficients) on their characteristics (Z, $\bar{Z}$ and $\hat{\lambda}$) had been the same as the returns (coefficients) on the characteristics of the non-adopters. The standard errors of equations (4) and (5) estimates are corrected using bootstrapping to account for first-stage estimation of the inverse Mills ratios. We followed a similar approach to generate the expected actual and counterfactual of maize production cost.

Taking the difference between equations (4) and (5) gives the average effect of technology on adopters, often described in the literature as the average treatment effect on the treated (ATT). The cost ATT estimation is also derived same way.

$$\begin{aligned}\mathrm{ATT}_{yj} &= E(Q_{itJ}/(j=J)) - (Q_{it0}/(j=J)) \\ &= (\beta_J^q - \beta_0^q)Z_{itJ}^q + (\sigma_J^q - \sigma_0^q)\hat{\lambda}_{itJ} + (\psi_J^q - \psi_0^q)\,\hat{\lambda}_{itJ}^q T + (\varphi_J^q - \varphi_0^q)\bar{Z}_{iJ}^q \end{aligned} \tag{6}$$

$$\begin{aligned}\mathrm{ATT}_{cj} &= E(C_{itj}/(j=J)) - (C_{it0}/(j=J)) \\ &= (\beta_J^c - \beta_0^c)Z_{itJ}^c + (\sigma_J^c - \sigma_0^c)\hat{\lambda}_{itJ} + (\psi_J^c - \psi_0^c)\hat{\lambda}_{itJ}^c T + (\varphi_J^c - \varphi_0^c)\bar{Z}_{iJ}^c \end{aligned} \tag{7}$$

The first two terms of equations (6) and (7) indicate yield change due to the difference in returns to observed characteristics and time-invariant unobserved characteristics, respectively, and the last two terms are attributed to yield changes because of time-varying unobserved heterogeneity difference.[5]

The ATT for yield and cost estimation generated from equations (6) and (7), in addition to serving to measure direct effects of technology adoption, will be used as an input in the economic surplus analysis model to compute the supply shift parameter (K-shift parameter).

2.2. *Estimation of economic surplus gains*

The effects of technology choice do not end at the level of adopters. Farm households supply part of their produce to the market and subsequently the direct effects of technology choices lead to an indirect effect on both other producers and consumers. We use an economic surplus (ES) model to examine the changes in consumer and producer surpluses.

The benefit of the technology to producers and consumers depends on how markets function. In the absence of external trade (a closed economy), the benefits of technology adoption are shared between producers and consumers. In a closed economy, a technology induced supply shift would reduce the equilibrium price. The Ethiopian

[5]In estimating production and cost functions, there is a problem of how to treat legumes in the case of maize-legume intercropping, particularly allocating the total inputs to each crop. One approach is to convert legume yield into maize equivalent using price as a weight and the maize-equivalent yield of legume added to the actual maize yield to provide total yield. However, this results in an artificial increase in maize production, which leads to a horizontal shift in the maize supply curve. Our approach considers revenue generated from legume production as a cost reduction for maize production (i.e. the revenue can serve to pay back inputs used for maize-legume production). This generates a vertical shift in the maize supply curve.

maize economy can be treated as a closed economy since the volume of maize exports and imports is below 1% of total supplies.

Evaluating the *ex-post* effects of adoption of technology requires estimating the K-shift parameter and counterfactual equilibrium price and maize volume production (i.e. price and maize production in the absence of the technology). The K-shift parameter is the proportionate vertical shift in the supply curve and/or the cost reduction per unit of output that is caused by changes in crop yield and cost of production (Alston *et al*., 1995). Measuring the K-shift parameter is a difficult task in the impact literature (Alston *et al*., 1995). Only a few impact assessment studies, such as Zeng *et al*. (2015), have used a statistically estimated K-shift parameter to estimate the economic surplus gains. To increase its accuracy and measure the true effects of adoption, the econometric approach described above enables us to capture determinants of yield and production costs, besides the independent effect of the technology itself. This is the major reason for combining the ES analysis with econometric methods. The K-shift parameter is expressed algebraically as follows (in the manner of Alston *et al*., 1995):

$$K = \left(\frac{\mathrm{ATT}_y}{\in} - \frac{\mathrm{ATT}_c}{1 + \mathrm{ATT}_y}\right) \times \text{Adoption rate(A)} \tag{8}$$

where ATT_y and ATT_c are the yield and cost ATT estimated from equations (6) and (7) but weighted by the adoption rate of each technology to arrive at the overall K-shift parameter. As shown in equations (6) and (7), there will be seven ATT estimates; that means estimating seven K-shift parameters. As there is one market for maize, an overall yield and cost ATT have been calculated using adoption level (A) as a weight to estimate the yield and cost ATT share contributed by a specific technology combination. The price supply elasticity value (ε) in equation (8) is, set at 0.5 (Abrar *et al*., 2004).

The K-shift parameter along with observed maize price (P^1) and other parameters are used to compute the counterfactual equilibrium price (P^0) that would prevail if the technology were not adopted, following Alston *et al*. (1995):

$$P^0 = P^1(\varepsilon + \eta)/(\varepsilon + \eta - K\varepsilon) \tag{9}$$

where η is the absolute price demand elasticity. The observed price P^1 is obtained as an average of national producer prices (FAOSTAT) over the period 2009–2012, US$ 0.199 per kg. Zeng *et al*. (2015) used a price demand elasticity value of 1, which we also use.

The counterfactual maize production (Q^0) is derived as a function of using observed maize quantity of production (Q^1) and change in maize yield due the technology (ATT_y), i.e.

$$Q^0 = \frac{Q^1}{(1 + \mathrm{ATT}_y)}.$$

Q^1 is represented by the 2009–2012 average observed quantity of maize production (5.3 million tons, FAOSTAT).

Assuming linear demand and supply curves (Alston *et al.*, 1995), changes in producer surplus (ΔPS) and consumer surplus (ΔCS) attributed to the new technology under a closed economy are calculated as follows:

$$\Delta \text{PS} = P^0Q^0(K - Z)(1 + 0.5Z\eta) \tag{10}$$

$$\Delta \text{CS} = P^0Q^0Z(1 + 0.5Z\eta) \tag{11}$$

where Q^0 is the counterfactual equilibrium quantity and Z is the relative change in price $Z = \left(\frac{P^0 - P^1}{P^0}\right)$ (Alston *et al.*, 1995). The total change in economic surplus (ΔES) is the sum of changes in producer and consumer surpluses.

2.3. Poverty impact analysis

In sub-Saharan Africa, growth in agriculture combats poverty on different fronts. First, most of the poor still depend on agriculture, thus any attempt to improve the sector benefits them. Second, enhancing agricultural productivity, particularly for staple crops such as maize, improves supply and reduces the staple food price, and in so doing helps to lift the poor (typically net consumers) out of poverty. Third, agriculture has stronger growth linkages with other sectors than other economic sectors, and thus creates employment opportunities for the poor along the value chain, thereby contributing to poverty reduction (De Janvry and Sadoulet, 2002; Christiaensen and Demery, 2007; Diao *et al.*, 2010).

Zeng *et al.* (2015) examined the implications of technology-induced economic surplus change on household poverty in Ethiopia using cross-sectional farm household survey data. Although their approach accounts for a technology-induced price effect on poverty, it fails to consider other indirect effects (such as employment creation along the value chain) with possible further implications for poverty. To account for direct and indirect effects of adoption on poverty reduction beyond the farm level, following Alene *et al.* (2009), we link the technology-induced change in economic surplus to poverty reduction based on a poverty reduction elasticity with respect to agricultural growth. The number of people who escape poverty at the current level of technology adoption is estimated as follows (Alene *et al.*, 2009):

$$P = \left(\frac{\Delta \text{ES}}{AgGDP} \times \delta\right) \times N \tag{12}$$

where P is the number of people who can be lifted out of poverty, ΔES is the change in total economic surplus due to technology adoption (and represents the social value of additional production), $AgGDP$ represents the value of agricultural gross domestic product, δ is the elasticity of poverty with respect to $AgGDP$ driven by growth of the staple crops, and N denotes the number of poor people in the country. We use a 3-year (2010/11–2012/13) average $AgGDP$ (US$ 12.7 billion) and the official poverty incidence for the same 3-year period from the national Bank of Ethiopia reports. The total population data (2010/11–2012/13) to derive number of poor people were obtained from the Central Statistics Bureau of Ethiopia from various annual reports.[6]

[6]The total population in 2010/11, 2011/12 and 2012/13 was 79.5, 82.1 and 84.3 million, respectively, while headcount ratio for same year was estimated at 29.6, 27.87 and 26%, respectively.

The poverty elasticity specific to staple crops was adopted from Diao *et al.* (2010), who estimated that a 1% annual increase in Ethiopia's GDP driven by staple crops growth leads to a 1.8% reduction in the country's poverty headcount rate per year.[7]

3. Study Area, Data and Descriptive Statistics

Our data come from two waves of comprehensive farm household surveys collected in 2010/11 and 2012/13 by the International Maize and Wheat Improvement Centre (CIMMYT) in collaboration with the Ethiopian Institute of Agricultural Research (EIAR). The survey covered 39 districts from the five regional states of Ethiopia covering various agro-ecologies (Figure S1, in the online Appendix). The first-round survey elicited information from 2,374 farm households, who had grown maize on 4,555 plots while the second-round survey collected information from 2,132 farm households, who had managed 3,914 maize plots.[8] Sample farm households were selected using multi-stage stratified sampling. First, maize growing districts were identified in each region. Second, three to six *kebeles*[9] were randomly chosen in the selected districts according to their population size. Third, 16 to 24 farm households in each selected *kebele* (proportional to their population size) were randomly chosen for face-to-face interviews with trained enumerators.

The surveys generated rich information at farm household, plot and village levels. The data include human capital variables (family size, education, age, the number of years living in a village), self-reported natural resource endowments (plot fertility, slope, depth, plot distance from homestead, plot tenure, plot size), agronomic practices (e.g. maize-grain legume intercropping, rotations), input use (seed, fertiliser, labour, other chemicals) and their associated costs, crops grown and output produced at plot level, physical capital ownership (livestock, farm size, major farm equipment and furniture), and distance to input distribution centres and agricultural information offices.

The dominant maize varieties used by 49% of sample households were hybrids, with 6% of sample farm households planting open pollinated varieties (OPV). We represent chemical fertiliser use as a dummy variable that indicates that a plot is treated with chemical fertiliser (Diammonium phosphate (DAP) + Urea). Legume diversification refers to a maize plot that is planted with legumes, either through rotation and/or intercropping.[10] In the study areas, the most widely used intercrop/rotated legume crop with maize is haricot bean.

These three improved technologies provide eight possible technology combinations from which farm households can choose (Table 1). Among the possible technology sets, combining improved maize seed with chemical fertiliser is the most popular, whereas improved maize seed with legume diversification is the least

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[7]Diao *et al.* (2010) also estimate that a 1% annual increase in Ethiopia's GDP driven by the agricultural growth leads to a 1.78% reduction in the country's poverty headcount rate per year.

[8]242 farm households were not interviewed during the second round survey because 56 households dropped from one of the regions due to budget constraint and the rest of households had either were not at home after two visits, left the village or were deceased.

[9]*Kebeles* are the lowest administrative unit in Ethiopia.

[10]We combine legume intercropping and rotation because there are no adequate observations to run separate regressions for each practice.

Table 2
Marginal and conditional probabilities of technology adoption

	D 2010	D 2013	F 2010	F 2013	V 2010	V 2013
$P(A_T = 1)$	11.3	16.4	54.5	62.5	52.4	59.1
$P(A_T = 1/A_D = 1)$	100	100	67.9	70.3	63.4	65.5
$P(A_T = 1/A_F = 1)$	14.1	18.5	100	100	75.6	80.1
$P(A_T = 1/A_V = 1)$	13.7	18.2	78.6	84.8	100	100
$P(A_T = 1/A_D = 1 \ \& \ A_F = 1)$	100	100	100	100	78	83
$P(A_T = 1/A_D = 1 \ \& \ A_V = 1)$	100	100	83.5	89.1	100	100
$P(A_T = 1/A_F = 1 \ \& \ A_V = 1)$	14.5	19.1	100	100	100	100

Note: Subscripts T, D, V and F denote type of technology, legume diversification, improved maize varieties and chemical fertiliser, respectively.

popular. The implied marginal and conditional probabilities of improved technologies are shown in Table 2, which indicates complementarity among technologies; adoption of one technology improves the likelihood of adoption of the other technology. The adoption of improved maize seed increases the odds of chemical fertiliser adoption and vice versa. This suggests that many farm households are aware of the complementary nature of improved maize seed and chemical fertiliser. Table 2 shows that legume diversification increased the likelihood of chemical fertiliser and improved maize seed adoption and vice versa. This does not, however, necessarily imply that it increased the intensity of chemical fertiliser use (see Table 3). Chemical fertiliser was the most widely adopted improved technology followed by improved maize seed. The adoption of improved technologies increased somewhat in the second-round survey.

Table 3 presents the intensity of input use, cost of production and yield patterns by technology set. Fertilisers were applied with improved maize seeds, but relatively smaller amounts of fertiliser were used with legume diversification, which is consistent with the nitrogen fixing properties of legumes, which thus reduce fertiliser costs. In addition, maize–legume intercropping generated additional revenue from legume production (Table 3). On average, the observed legume revenue (subtracting costs of seed and labour for harvesting and threshing) is ETB 4,714–7,583 per hectare.[11]

The cost of labour (both family and hired labour) formed the largest share of total costs of maize production followed by fertiliser and seed (Table 3).[12] Other costs (herbicides, insecticides, manure and tractor) were small. The survey data show higher maize yields with improved technologies.

Time period and regional dummy variables are included in both yield and cost functions to capture temporal and spatial differences in agro-ecology, price and institutions. Table 4 presents the descriptive statistics of these and other variables included in the analysis.

[11]1 US$ = 16.11 Ethiopian local currency (ETB) on average during survey periods.

[12]Following Jacopy (1993), the wage for family labour is generated by estimating a maize production function (see Table S1(E) in the online Appendix).

Table 3
Input use, cost of production, maize yield by technology set choices and plot characteristics (mean)

	$F_0V_0D_0$	$F_0V_0D_1$	$F_1V_0D_0$	$F_0V_1D_0$	$F_1V_0D_1$	$F_0V_1D_1$	$F_1V_1D_0$	$F_1V_1D_1$
Maize yield (kg/ha)	2,240	2,425	2,766	2,489	3,320	2,894	3,250	4,122
Fertiliser (kg/ha)	0	0	176	0	137	0	207	172
Labour (person days/ha)	80	78	84	77	83	73	85	80
Oxen power (oxen days/ha)	20	19	21	20	16	14	17	15
Total cost (ETB/ha)	3,607	4,650	6,105	3,659	5,901	3,886	6,590	6,412
Fertiliser cost (ETB/ha)	-	-	1,618	-	1,502	-	2,160	1,916
Other costs (ETB/ha)	52	66	54	83	39	136	82	49
Seed cost (ETB/ha)	156	129	286	343	476	338	517	574
Labour cost (family and hired) (ETB/ha)	3,398	3,776	3,887	3,233	3,883	3,412	3,837	3,748
Legume revenue (less seed & labour cost for harvesting & threshing) (ETB/ha)	0	6,648	0	0	6,972	4,714	0	7,583
Plot distance to residence (walking minutes)	8.88	6.32	11.29	12.31	8.82	14.16	12.91	13.88
Plot ownership (1 = owned)	0.94	0.98	0.91	0.92	0.89	0.95	0.88	0.94
Soil fertility (1–3: good-average-poor)	1.48	1.59	1.61	1.50	1.57	1.65	1.65	1.56
Plot slope (1–3: gentle-average-steep)	1.36	1.50	1.39	1.25	1.32	1.25	1.39	1.29
Soil depth (1–3: shallow-average-deep)	2.23	2.14	2.26	2.35	2.11	2.40	2.32	2.24
Manure/compost use (1 = yes)	0.83	0.82	0.79	0.88	0.77	0.92	0.80	0.75
Plot shock (1 = natural shock on a plot)	0.32	0.31	0.31	0.40	0.28	0.38	0.32	0.43

Note: ETB is Ethiopia local currency (1 USD ≈ 16.11 Birr on average during survey periods).

Table 4
Household and village level characteristics (mean)

Variable	$F_0V_0D_0$	$F_1V_0D_0$	$F_0V_1D_0$	$F_0V_0D_1$	$F_1V_1D_0$	$F_1V_0D_1$	$F_0V_1D_1$	$F_1V_1D_1$
Household-level variables								
Family size (number)	6.73	6.76	7.12	7.80	7.61	7.63	8.17	7.99
Head education (years)	2.98	3.45	2.72	2.94	4.64	3.93	3.95	4.41
Head sex (1 = male)	0.89	0.88	0.89	0.93	0.97	0.93	0.97	0.96
Head age (years)	50.46	50.56	48.79	51.20	48.83	48.01	47.79	48.20
Livestock asset (TLU)	3.60	2.70	3.76	3.66	3.71	3.57	4.70	3.60
Credit constrained household (1 = yes)	0.37	0.30	0.47	0.42	0.47	0.49	0.68	0.62
Asset value, ETB	1,699.19	2,587.88	143,063.70	3,804.93	8,913.04	5,484.28	4,445.48	4,589.11
Year (1 = 2013)	0.68	0.67	0.82	0.88	0.92	0.91	0.94	0.96
Village-level variables								
Distance to input distribution centre (walking minutes)	109.39	89.43	110.98	121.98	98.38	109.89	132.75	107.40
Distance to agricultural information centre (walking minutes)	35.66	36.67	38.73	45.37	35.87	39.70	49.63	36.02
Fertiliser price (ETB/kg)		10.10			10.69	10.94		12.54
Wage (ETB/person-days)	33.41	34.34	34.22	33.57	35.63	34.01	34.10	35.41
Seed price (ETB/kg)	5.28	11.87	15.31	5.64	21.88	9.87	19.69	23.10
Oromiya region	0.74	0.57	0.63	0.82	0.72	0.61	0.68	0.49
Benishang-gumuz region	0.17	0.10	0.20	0.09	0.04	0.09	0.08	0.03
Southern region	0.09	0.16	0.13	0.12	0.27	0.31	0.29	0.55
Amhara region	0.11	0.20	0.22	0.01	0.19	0.06	0.03	0.02
Tigray region	0.02	0.18	0.00	0.01	0.01	0.05	0.00	0.00
Observations	2,108	919	664	241	3,064	149	92	628

Note: ETB refers to Ethiopian local currency (1 US$ = 16.11 ETB during survey periods).

4. Results and Discussion

Our primary objective is to estimate the impacts of technologies adoption. We thus do not discuss our endogenous switching regression estimates, which are presented in the online Appendix (see Tables S1(B)–S1(D)). However, we note that in some of the outcome equations, the inverse Mills ratios, the mean of time varying variables and interaction of time period dummy with Mills ratios are significant, indicating the presence of sample selection in technology set choice.

4.1. Adoption impact on yield and production costs

Tables 5 and 6 present the actual and counterfactual yield and cost estimates and the average treatment effect (ATT) on adopters. Results show that there are significant maize yield and production cost differences between maize plots planted with a set of technologies and those plots planted without these technologies. The greatest impact is observed when these technologies are used jointly. Maize yield is 13.1 percentage points higher (ATT divided by average counterfactual yield value) with legume diversification technology ($F_0V_0D_1$), after controlling for other determinants of yield (Table 5).[13] Similarly, the technology set that consists of only improved maize seeds ($F_0V_1D_0$) or only chemical fertiliser ($F_1V_0D_0$) enhances maize yields by 13.2% and 22.2%, respectively. Moreover, the results show that combining both improved seeds and chemical fertiliser enhances maize yield by 38.7 percentage points. The adoption of all improved technology sets can enable the farmers to enjoy the greatest maize yield increase (97.8%).

Among the technology sets considered, crop diversification appears to be (relatively) the cheapest technology option to produce maize (Table 6) – which in part

Table 5

Impact of technology set choices on maize yield (kg/ha)

Technology set	Outcome by adoption status: Actual outcome (maize yield if household adopt technology set choice *j*)	Counterfactual outcome (maize yield if household did not adopt technology set choice *j*)	ATT
A	B	C	D=B–C
$F_1V_0D_0$	2,281.62	1,865.94	415.68 (33.75)***
$F_0V_1D_0$	2,058.83	1,818.04	240.79 (43.63)***
$F_0V_0D_1$	2,063.17	1,823.48	239.72 (79.85)**
$F_1V_1D_0$	2,729.89	1,968.73	761.15 (53.07)***
$F_1V_0D_1$	2,856.28	1,868.36	987.92 (148.31)***
$F_0V_1D_1$	2,723.41	1,820.21	903.30 (155.40)***
$F_1V_1D_1$	3,548.78	1,793.74	1,755.05 (54.28)***

Note: Standard errors in parentheses; ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

[13]We also estimate the outcome questions using random effects in Mundlak's framework and assuming balanced panel data. Results are qualitatively similar (not reported here) as in unbalanced panel model estimations.

Table 6
Impact of technology set choices on maize costs of production (ETB/ha)

Technology set	Outcome by adoption status: Actual outcome (maize production costs if household adopt technology set choice *j*)	Counterfactual outcome (maize production costs if household did not adopt technology set choice *j*)	ATT
$F_1V_0D_0$	5,261.07	3,415.33	1,845.74 (77.09)***
$F_0V_1D_0$	3,211.87	3,086.04	125.83 (59.14)**
$F_0V_0D_1$	2,981.73	3,242.15	–260.42 (168.54)
$F_1V_1D_0$	5,954.76	3,669.81	2,284.95 (65.52)***
$F_1V_0D_1$	4,246.74	3,560.95	685.79 (258.54)***
$F_0V_1D_1$	3,145.95	3,234.30	–88.34 (273.30)
$F_1V_1D_1$	4,194.03	3,876.75	317.28 (90.14)***

Note: Standard errors in parentheses; ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$

reflects our specification because we subtracted the revenue generated from legumes from the total cost of production. On the other hand, maize production with both improved maize seeds and chemical fertiliser was relatively the most expensive, due to dependence on purchased seed and chemical fertiliser ($F_1V_1D_0$). Our results also suggest that maize production could be made relatively cheaper by integrating improved seeds and chemical fertiliser with legume diversification. For instance, maize production costs with a fertiliser technology set ($F_1V_0D_0$) (+54%) can be reduced to 19.3% when it is combined with legume diversification ($F_1V_0D_1$). This reduction reflects positive interactions, e.g. legume diversification can reduce pests, diseases and weeds infestations, and legumes also fix nitrogen, thus reducing the demand for pesticides and chemical fertiliser, which (apart from labour) is the greatest cost item. A simple gross margin analysis reveals that adopters reap a significant net crop income and that higher net income is obtained from adoption of a combination of technologies (Table 7).[14] Recent empirical evidence (Teklewold *et al.*, 2013; Kassie *et al.*, 2015b; Manda *et al.*, 2016) in Ethiopia and elsewhere also demonstrate that a combination of technologies (including those used in this paper) provide higher net maize income than when only a single technology is adopted.

Impacts of adoption at the market level

The above ATT estimates for yield and cost are used to examine impacts of adoption on economic surplus changes that were used as an input to estimate poverty impacts of adoption. The weighted ATTs on adopters' yield and cost of production are 32% and 39.3%, respectively.

[14]Authors have a draft paper that shows the impact of a combination of technologies on net crop income using the same panel data as used in this paper. Table 7 figures are not directly comparable with those in Table 6, which are based on the regression results, and are also adjusted for legume revenue.

Table 7

Farm-level economic benefit of maize and legume production by technology set choices

Parameter	$F_0V_0D_0$	$F_1V_0D_0$	$F_0V_1D_0$	$F_0V_0D_1$	$F_1V_1D_0$	$F_1V_0D_1$	$F_0V_1D_1$	$F_1V_1D_1$
Gross value of crop production (ETB/ha) (A)	7,274	9,503	8,820	8,971	11,437	11,273	10,497	14,177
Variable costs including family labour (ETB/ha) (B)	3,607	6,105	3,659	4,651	6,590	5,901	3,886	6,412
Net crop income (A – B)	3,667	3,398	5,151***	4,320*	4,847***	5,372***	6,611***	7,765***
Variable costs excluding family labour (ETB/ha) (C)	252	2,099	528	287	2,964	2,103	621	2,737
Net crop income (A – C)	7,022	7,404*	8,292***	8,684***	8,473***	9,170***	9,876***	11,440***

Note: Gross value crop production refers to maize and legume whenever there is diversification (D); *, and *** denotes significance level at 10% and 1% levels. The comparison is made without the technology adoption scenario ($F_0V_0D_0$).

The combination of a 32% average yield increase and a 39.3% average cost increase generate a 26.4% cost reduction per kilogram of maize output (K-shift parameter). The estimated counterfactual maize price and volume of maize production are US$ 0.223 and 4.0 million tons, respectively. Assuming a closed economy, the 26.4% cost reduction per kilogram of maize output would result in US$ 245 million change in total economic surplus (US$ 140 and 105 million increases in producer[15] and consumer surpluses, respectively) at the current level of adoption.[16] The higher benefit to producers reflects the closed economy model assumption combined with the relative sizes of the demand and supply elasticities and the parallel supply shift assumption.[17]

Assuming the estimates hold true in our context and considering the change in total economic surplus gains as an additional income to *AgGDP*, the number of poor people who can escape poverty is estimated to be 788 thousand per annum in the country[18] or 3.5% of poor people in the country, which is 22.8 million.

5. Summary and Conclusions

Improved technologies adopted to produce staple crops such as maize could have profound indirect effects on both producers and consumers through market impacts. There have been relatively few studies that have attempted to measure the economic and social effects of multiple technology sets used for maize production by considering their indirect effects. Using two rounds of data from a large comprehensive household survey in Ethiopia, we evaluated both the farm- and market-level impacts of adoption of multiple technologies (improved maize varieties, fertiliser use and legume intercropping/rotation). We use a combination of econometric techniques and economic surplus approaches to achieve these objectives.

To address sample selection and unobserved heterogeneity often associated with survey data, we employed a multinomial switching endogenous regression model and exploited the panel nature of the data following Mundlak (1978). Our results support the presence of both time-varying and constant unobserved heterogeneity that affect both technology set choices and outcome variables (yield and cost of production), implying the importance of controlling selection bias in evaluating technology sets. The average treatment effect (ATT) results show that all the technologies have positive and significant impacts on maize yields, but combinations of technology provide the highest payoffs. Diversifying maize with legumes appears as the cheapest option for maize production.

The market-level impact analysis shows that the change in maize yield and costs of production due to adoption generate a 26.4% cost reduction per kilogram maize output on average. Based on the current level of adoption, domestic market structure

[15]The increase in producer surplus would be US$ 223 million if an open economy model was assumed.

[16]The K-shift parameter would have been 20.8% without subtracting grain legume intercropping revenue from maize costs of production and this produces a total economic surplus benefit of US$ 187 million. Further, if we lower the price elasticity of supply to 0.4, the K-parameter would rise to about 38.7%. Thus, the total economic surplus would increase to about US$ 376 million and producers would claim the largest share.

[17]We thank an anonymous referee for suggesting this point.

[18]This is equivalent to 718 thousand per year under a small open economy assumption.

and the volume of maize production, technology-induced cost reduction leads to an increase in producer and consumer surplus gains of US$ 140 and 105 million per annum, respectively. Furthermore, we found that the technology sets reduce the number of poor people by an estimated 788 thousand per annum. This study indicates that development policies that aim to promote integration of agricultural technologies have substantial impacts on improving economic growth, food security and reducing poverty in Ethiopia.

Some caveats on this study are appropriate. There are limitations to the way we identify and measure technologies. In our study, improved seed technology was an indicator variable that differentiated whether a seed is a local variety or improved variety. However, both improved and local seeds comprised different seed varieties with varying degrees of yield and seed price. Similarly, chemical fertiliser technology was identified as a dummy variable that denoted whether chemical fertiliser is applied on a plot without regard to the intensity or timing of application. Legume diversification was also a dummy variable that indicated whether maize crop was diversified with legumes, but we did not distinguish the type of diversification (temporal or spatial) or intensity of diversification (proportion of area covered by legumes). Second, our economic surplus analysis is based on the impacts of technologies on crop yield and costs of production. Technology adoption could, however, provide additional benefits such as risk management (e.g. Di Falco and Veronesi, 2014; Kassie *et al.,* 2015c) and environmental benefits (e.g. Teklewold *et al.*, 2013). Thus, our results should be taken as indicative rather than definitive. Nevertheless, these results do confirm the positive impacts of improved technologies associated with maize production on poverty alleviation in Ethiopia.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Distribution of sample districts where the survey was conducted.

Table S1. (A) Chow test statistics; (B) Drivers of adoption; (C) Maize yield determinants (kg/ha); (D) Maize costs of production determinants (ETB/ha); (E) Production function estimation for computing marginal value of family labour (fixed effects estimation; dependent variable: Ln(maize yield, kg/ha).

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