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Farm technology adoption in Kenya: a simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions

Maurice J Ogada[1*], Germano Mwabu[2†] and Diana Muchai[3†]

* Correspondence:
ogadajuma@yahoo.co.uk
†Equal contributors
[1]International Livestock Research Institute (ILRI), P.O. Box 30709-00100, Nairobi, Kenya
Full list of author information is available at the end of the article

Abstract

This paper models inorganic fertilizer and improved maize varieties adoption as joint decisions. Controlling for household, plot-level, institutional and other factors, the study found that household adoption decisions on inorganic fertilizer and improved maize varieties were inter-dependent. Other factors found to influence the adoption of the two technologies were farmer characteristics, plot-level factors and market imperfections such as limited access to credit and input markets, and production risks. Thus, easing market imperfections is a pre-requisite for accelerating farm technology adoption among the smallholders. Inter-dependence of farm technologies must also not be ignored in farm technology adoption promotion initiatives.

Keywords: Technology adoption; Simultaneous estimation; Africa; Kenya

JEL Classification: Q10; Q16; O55

Background

The Green Revolution which dramatically boosted the yield of cereals in Asia and Latin America is a clear manifestation of the potential of agricultural technologies in improving people's lives especially in the developing world (Pray, 1981). Indeed, it is the basis of support for Green Revolution in Africa by such philanthropic organizations as the Rockefeller and the Gates foundations. Successful agricultural transformation, the World over, has been largely attributed to improved farm technologies such as fertilizer, improved seeds and soil and water conservation (Johnston and Kilby, 1975; Mellor, 1976; Gabre-Madhin and Johnston 2002). Adoption of these technologies provides opportunities for increasing not only agricultural productivity but also incomes (Feder *et al.*, 1985). For developing countries, the contribution of improved technologies to agricultural productivity is well documented (see Sunding and Zilberman, 2001; and Doss, 2006 for details).

With the support of development partners, the government of Kenya has introduced or implemented several efficiency and productivity-enhancing technologies, programmes and projects at household level. Among the projects and programmes are the Kenya Agricultural Productivity Project (KAPP), the National Agriculture and Livestock Extension Programme (NALEP), the Agriculture Sector Programme Support (ASPS) and the National Accelerated Agricultural Inputs Access Programme (NAAIAP). Improved technologies for soil and water conservation, improved storage facilities, labour-saving and improved seeds have also been developed and disseminated, particularly by the Kenya Agricultural Research Institute (KARI).

Despite the efforts by the government and development partners, levels of technology adoption remain low (Republic of Kenya 2007; Ogada et al. 2010). While average adoption rates of improved maize varieties and inorganic fertilizer of 65 per cent and 76 per cent, respectively, appear impressive, great variations exist across regions and agro-ecological zones. The adoption rates are as low as 12 per cent for fertilizer (Olwande et al. 2009) and 30 per cent for improved maize varieties (Alliance for a Green Revolution in Africa 2010) in some regions. They are even worse, hardly 10 per cent, for other improved seed varieties (Alliance for a Green Revolution in Africa AGRA 2010). Given the link between technology adoption and farm productivity, and the desire by the Government of Kenya to promote development and adoption of agricultural technologies (Republic of Kenya 2007), understanding the factors that influence adoption of new and/improved technologies across households and communities is of urgent interest.

Previous studies have treated improved maize varieties and inorganic fertilizer as independent technologies, adopted independently (see Makokha *et al*., 2001; Ouma *et al*., 2002; Wekesa *et al*., 2003; Olwande et al. 2009; and Ogada et al. 2010). If simultaneity in decision-making exists, this approach yields biased, inefficient and inconsistent estimates (Maddala, 1983; Greene, 2003). This paper overcomes this problem by employing bivariate model which captures the inter-dependence of the two decisions. Various factors, which are not necessarily obvious to researchers, can simultaneously affect adoption decisions between improved maize varieties and inorganic fertilizer. For instance, the two could have synergies in farm production. As a result, the farmer who adopts an improved maize variety could most likely adopt inorganic fertilizer. What this implies is that the farm households could be adopting technologies as a package, say improved maize variety with complementary element as inorganic fertilizer and pesticides (Kabila et al. 2000). Besides methodological novelty, this paper incorporates GIS-generated measures of location and space in the analysis unlike the previous studies which relied on use of dummy variables.

The remainder of the paper is organized as follows: section 2 explores empirical literature on improved farm technology adoption; section 3 discusses the methods employed; section 4 presents and discusses the results; and section 5 concludes and infers policy implications.

Brief review of literature

Empirical works on determinants of agricultural technology adoption have mainly focused on risk and uncertainty (Koundouri et al. 2006; Simtowe *et al.*, 2006), asymmetry of information, institutional constraints, human capital, access to inputs (Feder et al. 1985; Foster and Rosenzweig, 1996; Kohli and Singh, 1997) and availability of supportive infrastructure as possible predictors of adoption decisions. More recently, however, focus has extended to social networks and learning. The literature is vast and may not easily be compressed. Therefore, this section reviews only a few relevant studies starting with those from other developing countries before moving to Kenya.

Kohli and Singh (1997) conducted a comparative study on adoption of high yielding varieties (HYVs) among states in India and concluded that rapid adoption of the HYVs in Punjab was as a result of cheap and easy access to the technology itself and the complementary inputs. As noted by McGuirk and Mundlak (1991) in their study in India using choice of technique framework, HYVs require high levels of fertilizer input and irrigation to realize the yield potential. Thus, complementary inputs must be available and affordable to enhance adoption of HYVs.

Another strand of literature focuses on social networks and learning. The basic argument here is that adoption of technologies is influenced by Bayesian learning. That is, initially only a few farmers may adopt, and even this group of farmers may do this just on smaller experimental scales. As the first harvest is realized, the farmers can update their belief about the technology which may increase the rate of adoption in subsequent years. Besley and Case (1993), for instance, used a model of learning in a situation where profitability of technology adoption was uncertain and beyond the farmer's control in India. They found that probability of adopting an agricultural technology increases as farmers realize the profitability of the new technology. Using a target-input model of new technology which assumes that the best use of an input is unknown and random, Foster and Rosenzweig (1995), and Conley and Udry (2002) found similar results. Foster and Rosenzweig (1995) studied adoption of HYVs in India while Conley and Udry (2002) studied application of fertilizer in pineapple cultivation in Ghana. These authors concluded that initial adoption may be low due to imperfect information on management and profitability of the new technology but as this becomes clearer from the experiences of their neighbours and their own experiences, adoption is scaled up. This is supported by Bandiera and Rasul (2006) who examined the link between social networks and technology adoption in Northern Mozambique and noted that a farmer who discussed agriculture with others had a higher propensity to adopt new technologies.

In Kenya, Gerhart (1975) examined adoption of hybrid maize between late 1964 and 1973 in western Kenya and noticed a rapid diffusion of the technology in the region despite constraints. Risk and uncertainty were identified as the greatest constraints to adoption of hybrid maize. Factors found to encourage adoption decision were farmer education, access to credit, and access to extension services. Farmers who adopted hybrid maize were found more likely to adopt other yield-enhancing practices such as use of inorganic and organic fertilizers, and modern management practices such as planting in rows, weeding more than once, thinning and using insecticides. Gerhart applied multivariate probit on cross-sectional data and supplemented it with qualitative techniques. The approach was theoretically sound because technology adoption decisions are inter-dependent and the decision to adopt one technology could enhance or deter adoption of other related technologies. However, the use of cross-sectional data ignores the dynamic aspects of household adoption behaviour which could make the work less suitable for policy. Moreover, the study examined only one region of the country.

Other studies in the country have followed the path of the seminal paper by Griliches (1957) on adoption of new agricultural technologies. Griliches examined heterogeneity of local conditions and how it affected adoption of hybrid corn in the mid-western United States. He noted the role of economic factors such as expected profits in influencing the variation in farm technology spread rates. He further noted that speed of adoption across geographical locations depended on the suppliers of the technology and suitability of the seed to local conditions. It is indeed from the work of Griliches that economic literature on agricultural technology adoption developed. Some of the factors that possibly explain the rate of adoption and the long-run equilibrium level of use of new agricultural technology as identified in the economic literature include: credit constraints, risk aversion, the farmer's landholding size, land tenure system, human capital endowment, quality and quantity of farm equipment, and supply of complementary inputs (Feder et al. 1985). Among the studies that have adopted this approach are Makokha *et al.* (2001), Ouma *et al.* (2002), and Wekesa *et al.* (2003). Makokha *et al*. (2001) examined determinant of adoption of fertilizer and manure in Kiambu District, focusing on soil quality as reported by the farmers. They found high cost of labour and other inputs, unavailability of demanded packages and untimely delivery as the main constraints to fertilizer adoption. Ouma *et al.* (2002) focused on adoption of fertilizer and hybrid seed in Embu District and found that agro-climate, manure use, cost of hired labour, gender of the farmer and access to extension services were important determinants of adoption. Wekesa *et al.* (2003) examined adoption of improved maize varieties and fertilizer in the coastal lowlands of Kenya and found that unsuitable climatic conditions, high cost and unavailability of seed, perceived soil fertility and low financial endowments were responsible for the low adoption. The above findings are consistent with those of the International Maize and Wheat Improvement Center (CIMMYT) studies as summarized by Doss (2007). Other cross-sectional studies, though focusing on different technologies such as dairy and soil and water conservation, have found similar results (see Nicholson *et al*., 1999; Ogada et al. 2010; Oostendorp and Zaal, 2011). These studies have three main limitations: they are based on cross-sectional data, they cover smaller geographical areas that cannot accurately reflect the diversity among farming communities and they use ordinary binary probit or logit which ignores the inter-dependence of agricultural technologies. Their results are, thus, likely to suffer endogeneity bias.

A study by Olwande et al. (2009)) used panel data to examine determinants of fertilizer adoption and intensity of use. Using a double-hurdle model, they found that age and education of the farmer, access to credit, presence of a cash crop, distance to fertilizer market and agro-ecological potential influence the probability of fertilizer adoption. Gender of the farmer, dependency ratio, credit access, presence of cash crop, distance to extension services and agro-ecological potential were found to influence intensity of fertilizer use. A double-hurdle model is useful in capturing intensity of adoption but it ignores the fact that adoption of fertilizer could also be influenced by related practices such as adoption of improved maize seed.

Overall, literature indicates that household demographic, location, socio-economic and institutional factors are important determinants of farm technology adoption and equilibrium level of use. But their effects may not be universal. A factor is universal if it promotes or impedes technology adoption irrespective of location and type of technology. Rubas (2004) tested the universality of age, education, outreach, and farm size in influencing adoption of agricultural technologies. Employing Ordinary Least Squares (OLS) and Minimum Absolute Deviation (MAD) approaches, the study found that education and farm size were positive universal (encourage adoption of all types of technology irrespective of location) while outreach was not universal. Age was not universal by OLS, and negative universal by MAD. The fact that universality of age, education and farm size was confirmed to be weak, one cannot assume that farm households in different locations respond to different technologies in the same way.

Methods

Theoretical model

Because households in Kenya and elsewhere in developing countries produce under uncertainty and great market imperfections, the study adopted expected utility maximization framework. Production risk was represented by the stochastic term, ε, whose distribution, G(.) was exogenous to the farm household's actions. Inorganic fertilizer and improved maize varieties being among the most important inputs in the smallholder's crop production process, the household's production function was presented as:

$$q_{it} = q\left(X_{it}^{f}, X_{it}^{s}, X_{it}^{o}, \varepsilon_{it}\right) \tag{1}$$

where X_{it}^{f} and X_{it}^{s} represent fertilizer and seed inputs by the household in a given year, respectively. X_{it}^{O} represent other inputs while ε_{it} represent production risk. This function was assumed to be well-behaved. Hereafter, the panel dimensions are suppressed for simplicity.

Letting r and p represent input and output prices respectively, the problem of a risk-averse household is to maximize expected utility of gross income expressed as:

$$\underset{X}{Max}\, E[U(\pi)] = \underset{X}{Max} \int_{0}^{q} \left[U\left(pq\left(X_f, X_s, X_o, \varepsilon\right) - r_f X_f - r_s X_s - r_o X_o\right)\right] dG(\varepsilon) \tag{2}$$

Where U(.)is the Von Neumann-Morgenstern utility function. E is the expectation operator while ε captures all the unobserved household heterogeneity such as unreported farm management ability, land fertility, risk preferences and risk management measures, and rate of discount which could affect input use and farm productivity.

Given that r and p are non-random, the first order necessary condition (FONC) for the fertilizer variable was specified as:

$$E\left(r_f U'\right) = E\left[p \frac{\partial q\left(X_f, X_s, X_o, \varepsilon\right)}{\partial X_f} U'\right] \tag{3}$$

And

$$\frac{r_f}{p} = E\left[\frac{\partial q\left(X_f, X_s, X_o, \varepsilon\right)}{\partial X_f}\right] + \frac{COV\left(U'; \partial q\left(X_f, X_s, X_o, \varepsilon\right)/\partial X_f\right)}{E\left(U'\right)} \tag{4}$$

where U' is the change in utility of income due to change in income. That is, $\frac{\partial U(\pi)}{\partial \pi}$. FONC for the other variables were derived using the same procedure. For risk-neutral households, the second term on the right hand side of Equation 4 would be equal to zero and therefore adoption of improved farm technologies would be dependent on the traditional marginal conditions. For the risk-averse households, the term would be different from zero and would measure deviations from the risk neutrality position. The term would be proportional and opposite in sign to the marginal risk premium with respect to the input under consideration (Koundouri *et al.*, 2006). In such a case, adoption of improved farm technology would be influenced by production risk besides the cost of technology adoption and farm-specific factors that may influence either technology performance or adoption costs.

Market imperfections made it important to include household characteristics and resource endowments in explaining farm household's investment and production decisions (Pender and Kerr, 1998). For example, labour market imperfections constrain a household's labour demand to its own labour supply with the result that only larger households are able to invest in labour-intensive technologies. Similarly, capital market imperfections restrict households to their savings and already accumulated capital assets such that poorer households are not able to invest in capital-intensive technologies. Generally, a household invests in a given improved farm technology if the expected utility with adoption, $E[U(\pi_{wa})]$, is higher than expected utility without adoption, $E[U(\pi_{-wa})]$. That is, when $E[U(\pi_{wa})] > E[U(\pi_{-wa})]$.

Antle (1983; 1987) provide a flexible way to estimate Equations 3 and 4 which only requires information on prices, input quantities and other observable variables. The approach equates maximizing expected utility of farm income with respect to any input to maximizing a function of moments of the distribution of ε. The moments themselves have X_f and X_s as arguments (Antle, 1983; 1987). This study, thus, computed the first three moments of the stochastic production function and included them as covariates in analysing adoption decisions for inorganic fertilizer and improved maize seed.

The study hypothesized that adoption decisions by a household on improved maize (HM_{ha}) and inorganic fertilizer ($fert_{ha}$) were interdependent. The decisions also depended on the profitability of the technology (P_f) as measured by proximity to market and access road, land ownership system (L_{os}), access to credit and market (A_{cm}), and household information on the improved technologies ($Info_h$). Other factors were plot characteristics (P_c), household characteristics (h_c), agro-ecological characteristics (AE_c), production risk (P_r) and other random factors (see Pender and Kerr, 1998; Shiferaw and Holden, 1999; Doss, 2007; Yesuf and Kohlin, 2008). The theoretical model of improved maize variety and inorganic fertilizer adoption decisions was, thus, specified as follows:

$$fert_{ha} = f\left(HM_{ha}, p_f, L_{os}, A_{cm}, Info_h, P_c, h_c, AE_c, P_r, \mu_{fert}\right) \tag{5}$$

$$HM_{ha} = f\left(fert_{ha}, P_f, L_{os}, A_{cm}, Info_h, P_c, h_c, AE_c, P_r, \mu_{HM}\right) \tag{6}$$

Equations 5 and 6 represent the observed binary variables which reflect the latent net benefits, $fert^*_{ha} and HM^*_{ha}$, from adopting inorganic fertilizer and improved maize variety, respectively.

Empirical model

As specified in the theoretical model (Equations 5 and 6), production risks are important in household decisions to adopt improved maize varieties and inorganic fertilizer. This is because farm households in low income countries are risk averse (Dercon, 2004). They suffer welfare erosion when their consumption and production fluctuate. This fluctuation may be captured by yield variability. However, it would be wrong to assume that the variance of production captures all the production risks to which households are exposed (Di Falco and Chavas, 2009). For instance, households are exposed to the downside risk (the risk of crop failure as measured by the skewness, with negative skewness implying greater exposure to crop failure). Analysis of adoption decisions was, therefore, done in two steps. In the first step, the first three sample moments of the maize yield distribution (mean, variance and skewness) were computed. In the second step, the estimated moments were included in the adoption models together with other explanatory variables.

The first step involved regressing maize yield in a given year against plot, household and village-level variables to obtain estimates of mean effects. The general functional form of the model was:

$$q_{it} = q(X_{it}, Z_{it}, \beta_1) + e_{it} \tag{7}$$

In estimating the yield-response function (Equation 7), we applied Guan *et al.* (2006) approach. This approach breaks the production function into two parts: the crop growth function and the scaling function. The crop growth function is specified as quadratic function instead of translog, commonly used in literature. Quadratic function is preferred to translog because it permits concavity and zero input. Concave yield-response curves are indeed consistent with most observable biological relationships. For instance, excess fertilizer or rainfall adversely affects crop growth. The scaling function incorporates facilitating inputs such as crop management practices, government programmes and household socio-economic attributes. This part of the production function is specified in exponential form which does not impose monotonicity on input–output relationship (Guan *et al.*, 2006).

The crop production model estimated, therefore, had the following general functional form:

$$y_{it} = G(X).F(Z) \tag{8}$$

where y_{it} is the maize yield realized by a household in a particular crop year, X is a vector of growth inputs, Z is a vector of facilitating inputs, G(.) is the crop growth function while F(.) is the facilitating or scaling function. Essentially, the crop growth function determines the attainable yield level given the biophysical environment while the interaction between the growth factors and the facilitating factors determines the actual yield. This explains why even farmers operating under similar agro-ecological conditions experience yield differences.

The quadratic crop growth part was specified as:

$$\begin{aligned} G_{it} = {} & \alpha_1 rain_{it} + \alpha_2 plantingfert_{it} + \alpha_3 dressfert_{it} + \alpha_4 manure_{it} + \alpha_5 rain_{it}^2 + \\ & \alpha_6 rain_{it} plantingfert_{it} + \alpha_7 rain_{it} dressfert_{it} + \alpha_8 rain_{it} manure_{it} + \\ & \alpha_9 plantingfert_{it}^2 + \alpha_{10} plantingfert_{it} dressfert_{it} + \alpha_{11} plantingfert_{it} manure_{it} + \\ & \alpha_{12} dressfert_{it}^2 + \alpha_{13} dressfert_{it} manure_{it} + \alpha_{14} manure_{it}^2 \end{aligned} \tag{9}$$

The scaling function was specified as:

$$\begin{aligned} F_{it} = {} & \exp\{-[\beta_0 + \beta_1 acres_{it} + \beta_2 flbmpha_{it} + \beta_3 flbfpha_{it} + \beta_4 flbcpha_{it} + \\ & \beta_5 headeducyrs_{it} + \beta_6 soccaplev + \beta_7 crpinc_{it} + \beta_8 mktdist]^2\} \end{aligned} \tag{10}$$

Overall, the maize yield function was expressed as:

$$\begin{aligned} maizpha_{it} = {} & \{\alpha_1 rain_{it} + \alpha_2 plantingfert_{it} + \alpha_3 dressfert_{it} + \alpha_4 manure_{it} + \alpha_5 rain_{it}^2 + \\ & \alpha_6 rain_{it} plantingfert_{it} + \alpha_7 rain_{it} dressfert_{it} + \alpha_8 rain_{it} manure_{it} + \alpha_9 plantingfert_{it}^2 + \\ & \alpha_{10} plantingfert_{it} dressfert_{it} + \alpha_{11} plantingfert_{it} manure_{it} + \alpha_{12} dressfert_{it}^2 + \\ & \alpha_{13} dressfert_{it} manure_{it} + \alpha_{14} manure_{it}^2\} \exp\{-\beta_0 + \beta_1 acres_{it} + \beta_2 flbmpha_{it} + \\ & \beta_3 flbfpha_{it} + \beta_4 flbcpha_{it} + \beta_5 headeducyrs_{it} + \beta_6 soccaplev + \beta_7 crpinc_{it} + \\ & \beta_8 mktdist]^2\} + f_i + e_{it} \end{aligned} \tag{11}$$

where f_i refers to unobserved household heterogeneity and e_{it} s the random error term assumed to be i.i.d.N(0, σ^2). All the other variables are defined in Additional file 1: appendix 1. $\alpha_1, \alpha_2, \ldots\ldots, \alpha_{14}$ and $\beta_0, \beta_1, \ldots, \beta_8$ are the parameters to be estimated.

The j^{th} central moment of the maize yield about its mean was, therefore, computed as:

$$e_j = e\left\{[q(.)-\mu]^j\right\} for\ j = 2, \ldots.., m \tag{12}$$

where μ is the mean maize yield or the first moment of maize yield per household. The estimated residuals from the mean regression were the estimates of the first moment of maize yield distribution. The estimates were then squared and regressed against the same variables as in Equation 13.

$$e_{it}^2 = q_2\left(X_{it}, Z_{it}, \hat{\beta}_2\right) + v_{it} \tag{13}$$

The least squares estimates of $\hat{\beta}_2$ are consistent and asymptotically normal (Antle, 1983). The predicted values of e_{it}^2 are also consistent estimates of the second central moment of maize production distribution. The same procedure was used to estimate the third central moment (skewness) of maize production distribution (in this case the estimated errors were raised to power three). In literature, this approach has been used by Antle (1983) and Koundouri *et al*. (2006).

The estimated production risk factors were then incorporated into the improved maize variety and inorganic fertilizer adoption models (Equations 14 and 15) which were estimated as bivariate probit to deal with simultaneity of technology adoption decisions. Similar approach has been used by Feder *et al*. (1985), Feder and Onchan (1987) and Yesuf and Kohlin (2008). The model was specified as follows:

$$fert_{ha}^* = \gamma_1 HM_{ha} + \alpha_1' X_1 + \varepsilon_f \ \ , \ fert_{ha} = 1 \begin{cases} if \ \ fert_{ha}^* > 0 \\ \\ 0 \ \ otherwise \end{cases} \tag{14}$$

$$HM_{ha}^* = \gamma_2 fert_{ha} + \alpha_2' X_2 + \varepsilon_H \ \ , \ HM_{ha} = 1 \begin{cases} if \ \ HM_{ha}^* > 0 \\ \\ 0 \ \ otherwise \end{cases} \tag{15}$$

$$\{\varepsilon_f, \varepsilon_H\} \tilde{}\ BVN\left\{(0,0), \sigma_f^2, \sigma_H^2, \rho\right\},$$

Where P is the correlation, σ_i^2 is the variance,$fert_{ha}^*$ and HM_{ha}^* are observed binary (latent) variables indicating the household's adoption status of fertilizer and improved maize. X_1 and X_2 are vectors of explanatory variables (including production risk factors), and ε_f and ε_H are the error terms for the respective equations.

The reduced form of the model required for consistent and efficient estimates was:

$$fert_{ha} = \pi_1' X + e_f \tag{16}$$

$$HM_{ha} = \pi_2' X + e_H, \tag{17}$$

$$\{e_f, e_H\} \tilde{}\ BVN\left\{(0,0), \sigma_f^2, \sigma_H^2, \tau\right\},$$

where τ is the correlation (measure of the extent to which the two errors covary), σ_i^2 is the variance, and X is the union of exogenous variables in the system. The correlation coefficient between the errors measures the extent of correlation between inorganic fertilizer and improved maize varieties adoption decisions. This arises if unobserved variables that affect adoption of inorganic fertilizer also affect adoption of the improved maize varieties. In the presence of such correlation, univariate probit yields biased estimates while bivariate probit technique produces consistent and fully efficient estimates (Greene, 1998). Bivariate probit model is estimated by maximum likelihood.

Coefficients of bivariate probit, just like those of other discrete choice models cannot be interpreted directly. They are transformed into marginal effects, interpreted as the change in predicted probability associated with the changes in the exogenous variables. Following Greene (1998), the marginal effects were computed as:

$$\frac{\partial BVN\left[\Phi\left(\alpha_1' X_1+\gamma_1,\alpha_2' X_2+\gamma_2,\rho\right)\right]}{\partial z_k}=\left\{\phi\left(\alpha' X_1+\gamma_1\right)\Phi\left[\left(\gamma_2' X_2-\rho\left(\alpha_1' X_1+\gamma_1\right)\right)/\right.\right.$$

$$\left.\left.\sqrt{1-\rho^2}\right]\right\}\alpha_z+\left\{\phi\left(\gamma_2' X_2\right)\Phi\left[\left(\left(\alpha_1' X_1+\gamma_1\right)-\rho\left(\gamma_2' X_2\right)\right)/\sqrt{1-\rho^2}\right]\right\}\gamma_z,$$

for fertilizer, and:

$$\frac{\partial BVN\left[\Phi\left(\alpha_2' X_2+\gamma_2,\alpha_1' X_1+\gamma_1,\rho\right)\right]}{\partial z_k}=\left\{\phi\left(\alpha' X_2+\gamma_2\right)\Phi\left[\left(\gamma_1' X_1-\rho\left(\alpha_2' X_2+\gamma_2\right)\right)/\sqrt{1-\rho^2}\right]\right\}\alpha_z+$$

$\left\{\phi\left(\gamma_1' X_1\right)\Phi\left[\left(\left(\alpha_2' X_2+\gamma_2\right)-\rho\left(\gamma_1' X_1\right)\right)/\sqrt{1-\rho^2}\right]\right\}\gamma_z$, for improved maize varieties. Φ is the normal cumulative distribution function. When $p = 0$ the expression reduces to: $\Phi\left(\alpha_2' X_2\right)\Phi\left(\alpha_1' X_1+\gamma_1\right)+\Phi\left(-\gamma_2' X_2\right)\Phi\left(\alpha_1' z_1\right)$.

Estimation challenges and remedies

For consistent estimates of production risks and determinants of adoption of improved maize varieties and inorganic fertilizer, it was important to control for unobserved heterogeneity (f_i) which might have been correlated with observed explanatory variables. Using household fixed effects could have been an option because household panel data were available. Unfortunately, the Guan *et al.* (2006) approach used to estimate production risks and the bivariate probit model used to estimate adoption are non-linear maximum likelihood models which cannot be directly estimated by fixed effects (Wooldridge, 2002). As a result, the study adopted Mundlak (1978) and Chamberlain (1984) approach. The approach involved including mean values of time-varying explanatory variables in Equations 11, 16 and 17. That is, the approach assumes that unobserved effects are linearly correlated with explanatory variables as expressed in Equation 18.

$$f_i=\tau+\gamma\bar{X}_i+\eta_i \tag{18}$$

where $\bar{X}_i$ is a vector of the mean of time-varying explanatory variables within each household, τ is a constant, γ is a vector of parameters and η_i ~i.i.d(0, σ_η^2) and is independent of e_{it},e_f and e_H . The vector γ is not different from zero if the observed explanatory variables are uncorrelated with the random effects.

Data

The study used the Tegemeo Agricultural Monitoring and Policy Analysis (TAMPA) household panel survey data. The survey is a collaboration project between Tegemeo Institute of Egerton University, Kenya, and Michigan State University of the United States. It aims at monitoring smallholder production patterns, consumption and incomes to identify policy agenda for farmers. It is geographically diverse and nationally representative of the rural maize-growing areas. The panel is based on the Kenya National Bureau of Statistics' (KNBS) agricultural sample frame. Only two waves of the survey, 2004 and 2007, were available to us with complete information on 1167 farm households. The waves contain detailed information on agricultural input and output, household consumption, income, demographics, location, infrastructure and credit information.

Summary statistics of the variables for bivariate analysis of technology adoption are provided in Tables 1 and 2. Adoption rates by survey years and broad agro-ecological zones (lowlands, midlands and highlands) are first examined (Table 1).

Adoption rates of inorganic fertilizer and improved maize varieties increased between the two survey periods for all the broad agro-ecological zones. However, the lowlands remained the lowest adopters of both technologies, recording only 3.8 per cent adoption rate for inorganic fertilizer and 38 per cent for improved maize varieties. For manure adoption, the highlands were the worst performers although this was appropriately compensated for by the high adoption of inorganic fertilizer. Notably, adoption rates of manure did not change between the periods of reference. The 3.8 per cent of households that adopted inorganic fertilizer in the lowlands in 2004 also adopted improved maize varieties. The same pattern was replicated in 2007 with 3.9 per cent of households adopting both technologies, an indication that out of the 7.7 per cent that adopted inorganic fertilizer most also adopted improved maize varieties. This provides a useful insight: those who adopt inorganic fertilizer are more likely to adopt improved maize varieties. Descriptive statistics of the other variables used in the analysis are provided in Table 2.

The adopting households exhibited certain characteristics over their non-adopter counterparts for the two technologies. They had higher levels education, and marginally higher average age. A larger proportion of these households were male headed, had soils with poor water-retention, and had more land under maize cultivation. On average, such households were also closer to input markets. On the production risks, these households experienced higher expected maize yield, higher yield variability and higher downside risk. In the 2004 survey, the adopting households reported a lower wage rate for farm labour than the non-adopter households. In 2007, however, reported wage rates were, on average, similar for the two categories of households.

Results and discussion

Estimation of the production function was useful only for generating production risks. The results are shown in Additional file 1: appendix 2. Focus of this section, therefore,

Table 1 Household adoption levels of fertilizer and improved maize varieties

Technology	2004			2007		
	LL	ML	HL	LL	ML	HL
I/fertilizer	3.8	60	86	7.7	63	89
Maize	38	60	83	39	65	88
Both	3.8	48	73	3.9	49.7	79.4
Manure	45	44	25	46	46	25
No. of observations	1167			1167		

LL = Lowland; ML = Midlands; HL = Highlands; I/fertilizer = Inorganic fertilizer

Table 2 Descriptive statistics of bivariate probit analysis variables

Variable	2004				2007			
	I/Fertilizer		I/Maize		I/Fertilizer		I/Maize	
	NA	A	NA	A	NA	A	NA	A
Age of household head (years)	52 (23)	54 (17)	53 (23)	53 (18)	52 (25)	54 (22)	50 (27)	54 (21)
Household head's education (0 = No education; 1 = primary level; 2 = secondary level; 3 = tertiary level)/fraction of households in each category								
0	0.37	0.18	0.36	0.19	0.36	0.23	0.40	0.22
1	0.46	0.49	0.48	0.48	0.47	0.46	0.43	0.48
2	0.15	0.26	0.13	0.26	0.15	0.24	0.14	0.24
3	0.02	0.07	0.03	0.07	0.02	0.07	0.03	0.06
Household size (No. of people in a household)	4 (2)	4 (2)	4 (2)	4 (2)	5 (3)	5 (3)	5 (3)	5 (3)
Acres (size of cropped land in acres)	1.4 (1.6)	1.5 (1.9)	1.3 (1.6)	1.5 (1.9)	1.2 (1.4)	1.8 (3.8)	1.2 (1.3)	1.7 (3.7)
Male-headed households (Proportion of male-headed household)	0.73 (0.44)	0.84 (0.37)	0.73 (0.44)	0.84 (0.37)	0.70 (0.46)	0.79 (0.41)	0.66 (0.47)	0.80 (0.40)
Credit access (proportion of households that received credit)	0.26 (0.09)	0.27 (0.11)	0.27 (0.09)	0.26 (0.11)	0.26 (0.08)	0.27 (0.11)	0.27 (0.10)	0.26 (0.11)
Market distance (distance from household to input market in kilometres)	7.2 (8.2)	5.6 (6)	6.7 (7.8)	6.0 (6.5)	7.3 (8.4)	5.6 (5.9)	6.4 (7.8)	6.2 (6.6)
Soil water retention (ability of soils to retain water. Captured through GIS)	0.7 (0.46)	0.88 (0.32)	0.74 (0.44)	0.85 (0.36)	0.69 (0.46)	0.88 (0.33)	0.74 (0.44)	0.84 (0.36)
Expected yield (mean maize yield)	407 (159)	943 (392)	510 (310)	857 (413)	517 (135)	1,002 (390)	590 (250)	936 (405)
Yield variance (maize yield variability as predicted from the production function)	259,796 (308,208)	457,116 (723,916)	285,004 (488,765)	432,982 (652,834)	289,302 (309,176)	415,752.5 (572,709)	274,432 (302,657)	415,070 (560,788)

Table 2 Descriptive statistics of bivariate probit analysis variables *(Continued)*

Downside risk (Skewness of the maize yield as predicted from the production function)	3.59D^{08} (1.88D^{09})	6.44D^{08} (4.13D^{09})	3.48D^{08} (2.71D^{09})	6.37D^{08} (3.76D^{09})	6.55D^{08} (1.86D^{09})	4.39D^{08} (3.35D^{09})	4.18D^{08} (1.70D^{09})	5.68D^{08} (3.32D^{09})
Wage rate (Daily wage rate of the farm labour in Kenya Shillings)	87 (40)	82 (32)	85 (41)	83 (32)	89 (37)	89 (29)	89 (36)	89 (30)
Number of observations	1167				1167			

Standard deviations in parentheses, I/Fertilizer = Inorganic fertilizer; I/Maize = Improved maize varieties; NA = Non-Adopters; A = Adopters.

is the results of the bivariate probit model of adoption of inorganic fertilizer and improved maize varieties. A joint significance test of the average terms rejected the null hypothesis, $H_0 : \gamma = 0$ (Equation 18) for the production function and the adoption Equations. This meant that the unobserved heterogeneity was correlated with the averages, $\bar{X}_i$. Mundlak-Chamberlain approach was, therefore, justified.

For all the models, the problem of multicollinearity was tested and found to be serious for variance and skewness (reflected in the variance inflation factor of 13.27 and 11.09, respectively). To solve the problem, skewness was dropped from the analysis and the test re-conducted. The test combined Variance Inflation Factor (VIF) and Eigen Values approaches. All the variance inflation factors were less than 2 and the condition number was 2.66, indicating that multicollinearity was no longer a problem.

Bivariate probit results are displayed in Table 3. The significance of LR test ($\rho = 0$) implies that adoption decisions about improved maize varieties and inorganic fertilizers are not independent. Both decisions are affected by the same unobservable heterogeneities. Thus, the decisions are jointly determined. This is plausible because fertilizer and improved maize varieties are complementary agricultural production technologies. Therefore, estimation of separate equations yields unreliable results. The finding is consistent with those of McGuirk and Mundlak (1991) and Kohli and Singh (1997).

The smallholders using manure in their crop production were six per cent less likely to adopt inorganic fertilizer. Such households were, however, seven per cent more likely to adopt improved maize varieties. Inorganic fertilizer and manure would be complementary in circumstances where there is under application of both but basically the two should be substitutes. Thus, farm households that have and apply sufficient quantities of manure would not apply inorganic fertilizer. This explains why both increase the probability of adopting improved maize varieties. For joint adoption of inorganic fertilizer and improved maize varieties, manure adopting smallholders had a six per cent lower chance than their non-adopting counterparts.

Education of the farm household's head was important in influencing joint adoption of the two technologies under consideration. Households whose heads had primary school level and secondary school level of education had four per cent and five per cent higher chance, respectively, than their uneducated counterparts. Positive correlation between education and technology adoption was also noted by Gerhart (1975). However, as indicated by Rubas (2004), universality of education in influencing technology adoption, though positive, is weak. Thus, it is not surprising that its influence is statistically insignificant for adoption of inorganic fertilizer and improved maize variety singly but significant for their joint adoption.

While the gender of the household head had no effect on adoption of the individual technologies, it weakly promoted joint adoption of the two technologies. Male-headed households had four per cent higher probability of adopting both inorganic fertilizer and improved maize variety than the female-headed households. This possibly indicates that female-headed households are more resource-constrained.

Increased regional access to agricultural credit is important in promoting adoption of inorganic fertilizer and joint adoption of inorganic fertilizer and improved maize variety. Improvement of credit access index by one per cent, improves the probability of households adopting inorganic fertilizer by 26 per cent and joint adoption of inorganic fertilizer and improved maize variety by 20 per cent. This is consistent with the findings

Table 3 Determinants of inorganic fertilizer and improved maize varieties adoption decisions

Variable	Inorganic fertilizer adoption		Improved maize varieties		Joint adoption
	Coefficient	Marginal effect	Coefficient	Marginal effect	Marginal effect
Technology Adoption					
Manure	−0.79*** (-6.04)	−0.06***(-3.68)	0.03 (0.31)	0.07*** (4.23)	−0.06***(-3.53)
Human and physical capital					
Head's age	−0.02** (-2.47)	0.001 (1.34)	0.001 (0.13)	−0.001 (-1.30)	−0.001(-1.03)
Head's age Sq	0.0002**(2.49)		−0.0001(-0.96)		
Head's education					
Primary	0.1 (0.75)	−0.02 (-1.28)	0.19**(1.97)	0.02(1.15)	0.04*(1.93)
Secondary	0.14 (0.84)	−0.03 (-1.53)	0.28**(2.21)	0.03(1.32)	0.05**(2.10)
Tertiary	0.18 (0.73)	−0.02 (-0.71)	0.24(1.29)	0.02(0.55)	0.05(1.48)
Male head	0.18 (1.24)	−0.01 (-0.70)	0.18 (1.61)	0.01(0.53)	0.04*(1.92)
Household size	−0.02 (-0.88)	−0.0001(-0.02)	−0.01 (-0.51)	0.0005 (0.13)	−0.003(-0.93)
Wage rate	−0.0002 (-0.09)	−0.00001 (-0.04)	0.0003 (0.16)	−0.0002 (-0.10)	−0.00004(-0.13)
Institutional factors					
Credit access	3.1*** (4.85)	0.26*** (4.14)	−0.39 (-0.92)	−0.31*** (-4.60)	0.20**(2.23)
Secure tenure	−0.08 (-0.97)	−0.04***(-4.18)	0.26*** (3.94)	0.04*** (4.08)	0.03**(2.33)
Market distance	−0.04*** (-3.05)	−0.001(-0.52)	−0.01** (-2.17)	0.001(0.99)	−0.01***(-3.42)
Plot and soil characteristics					
Fast-drained soils	0.86*** (6.75)	0.02(1.38)	0.29*** (3.12)	−0.03 (-1.58)	0.11***(6.44)
Plot Size (acres)	0.39*** (6.89)	0.01(0.79)	0.14*** (2.75)	−0.01(-1.59)	0.05***(5.87)
Plot size (acres) Sq.	−0.004***(-4.49)		0.0004(0.18)		
Year 2007	−0.14 (-1.55)	−0.03***(-2.83)	0.14**(2.27)	0.03***(2.82)	0.01 (0.74)
Production Risks					
Expected yield	0.004*** (11.60)	0.0002*** (6.64)	0.001*** (3.24)	−0.0002*** (-7.90)	0.0004***(11.45)
Variance	$-3.63D^{-07}$*** (-2.57)	1.32D (0.01)	$-1.73D^{-07}$* (-1.94)	$6.01D^{-09}$ (0.46)	−5.47D-08***(-2.73)
Means of time-varying variables					
Mean head age	0.002 (0.33)		0.002(0.40)		
Mean acres	−0.26*** (-4.48)		−0.12**(-2.34)		
Mean wage	−0.002 (-0.58)		0.003 (1.43)		
Mean household size	0.03 (0.76)		0.017 (0.62)		
Mean expected yield	0.002*** (6.26)		0.002***(7.59)		
Mean variance	$-4.13D^{-07}$*(-1.79)		$5.96D^{-08}$(0.45)		
Intercept	−4.41*** (-12.64)		−1.87*** (-8.27)		
LR test ($\rho = 0$)	$\chi^2(1) = 19.9$***		$\chi^2(1) = 19.9$***		
No. of Observations	2334		2334		

***, ** and * indicate significance at 1%, 5% and 10%, respectively; figures in parentheses are Z-scores.

of Feder et al. (1985) and Olwande et al. (2009) Smallholders may not be able to accumulate sufficient savings to purchase relatively more expensive technologies like inorganic fertilizer or combined inorganic fertilizer and improved maize variety. On the contrary, increased credit access lowers the probability of adoption of improved maize variety as an individual technology. This implies that access to credit could make smallholders switch to higher value crops.

Land tenure security is important in influencing adoption of improved maize variety and joint adoption of inorganic fertilizer and improved maize variety. Households with secure land tenure had four per cent higher probability of adopting improved maize variety and three per cent higher chance of adopting combined inorganic fertilizer and improved maize variety than their counterparts with insecure land tenure regime. While it is not explicit from our data, it is possible that secure tenure enables households to lease out part of their landholding for some cash for purchase of the improved technologies.

Distance to input market was negatively correlated with joint adoption of inorganic fertilizer and improved maize variety. A household which is one kilometre closer to the input market had one per cent higher chance of adopting both inorganic fertilizer and improved maize variety than its counterpart one kilometre away. Most probably this is due to easier access to these technologies by farm households closer to the markets. Households located far from markets essentially incur higher costs of adoption due to transport charges.

Households whose plots were well-drained had 11 per cent higher chance of joint adoption of inorganic fertilizer and improved maize varieties than households with poorly drained plots. Well-drained soils are highly vulnerable to erosion and leaching. This could substantially reduce their fertility, increasing the need to adopt improved technologies to enhance output. This is consistent with Wekesa *et al.* (2003).

The size of plot cultivated by the household was positively correlated with joint adoption of the two technologies. An increase of a household's cultivated land area by one acre, on average, increased the probability of joint adoption of inorganic fertilizer and improved maize varieties by five per cent. Literature attributes positive influence of plot size on improved technology adoption to confounding factors such as poor soil quality, fixed costs of adoption, credit access and risk preferences (Feder et al. 1985). This study controlled for the confounding factors but plot size was still significant in positively influencing probability of adoption of the two technologies. This supports the Neo-Malthusian hypothesis that land redistribution and fragmentation arising from population pressure does not lead to more intensification of farming.

While time had influence on the adoption of the individual technologies, it had no effect on joint adoption of the two technologies. Relative to 2004, the 2007 adoption of inorganic fertilizer was three per cent lower. The reverse was true of improved maize variety adoption.

Expected higher yield enhanced probability of adoption of inorganic fertilizer and joint adoption of inorganic fertilizer and improved maize variety. On the contrary, highly variable yield lowered probability of joint adoption. This indicates that smallholders are risk averse and would be hesitant to invest in highly uncertain activities. Negative influence of risk and uncertainty on farm technology adoption has previously been noted by Gerhart (1975), Koundouri et al. (2006) and Simtowe *et al.* (2006).

Conclusion and policy implications

Stagnating agricultural productivity has been a major policy concern in Kenya. It has led to increased investment in development and dissemination of yield-enhancing technologies. Remarkable success has been recorded in adoption of inorganic fertilizers and improved maize varieties although wide disparities remain across geographical areas. For other improved crop varieties, adoption levels remain very low, barely 10 per cent of the farm households. Thus, this study sought to understand the drivers of adoption of improved farm technologies among the smallholder food crop farmers in the country. It examined bivariate adoption of inorganic fertilizer and improved maize varieties to control for unobservable household heterogeneities in adoption decisions.

The study found that decisions to adopt complementary technologies are interdependent. It further established that plot-level, household-specific factors, and market imperfection are important in influencing the likelihood of a household adopting inorganic fertilizer and improved maize varieties. Among the key factors in this regard include education level of the household head, plot size operated by the household, land tenure security, distance to the input market, water-retaining capacity of the plot, access to credit, manure adoption, expected yields and yield variability.

The above results have important policy ramifications. Foremost, it is important to consider the complementarity of different agricultural technologies in promotion of their adoption. For instance, smallholders may be hesitant to adopt improved maize varieties if they are unable to obtain fertilizer to go with it. Thus, to promote adoption of complementary technologies, it is important to ensure that the technologies are available and affordable to the smallholders. For example, it may not be useful to subsidize one of the technologies without due consideration of the famers' capability to fully fund the remaining parts of the cost of adoption.

Although larger plots attract adoption of inorganic fertilizer and improved maize varieties, it may not be possible to curtail further sub-division of agricultural land as population increases. One option could be to increase access to land through land rental market to enable land-constrained smallholders acquire additional farmland. This is possible through land banks. Another option, though achievable only in the long term, is to expand the industrial sector to absorb more people from the agricultural sector to reduce pressure on agricultural land.

Improved technologies should be availed within easy reach of the farming households. While the government can contribute to this by improving transport infrastructure within the farming villages, the technology producers and marketers have the most important role of setting up distribution outlets closer to the farming communities. Local farmer organizations may also contribute through bulk buying of the improved technologies and directly supplying the same to the members in appropriate quantities.

To deal with the influence of yield and yield variability on farm technology adoption, it is important to ensure that the yield-enhancing technologies are able to increase yields substantially and maintain the high yields. Thus, when a technology is associated with high risks that may lead to extreme yield fluctuations, it may be useful to insure the farmers against such risks to encourage adoption. Index-based crop insurance is an option that could be explored.

Setting up smallholder credit scheme, especially for purchase of farm technologies, could be an important step towards accelerating farm technology adoption. Because the smallholders may not be able to acquire credit from the mainstream financial sector due to the risky nature of their business, the government could step in either as a guarantor or as a direct provider of the funds through, say microfinance institutions. An alternative approach could be to mobilize the smallholders to form organizations through which to pool resources and obtain additional funding from either the government or financial institutions. Whichever approach is chosen, the funds should be low-interest and easily accessible.

The above policy implications are short-run remedial measures. Long-run solutions, however, lie in correcting market imperfections. This is only possible with broad-based economic development.

Additional file

Additional file 1: Appendices.

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
MJO carried out econometric analysis and drafted the results chapter. GM conceptualized the study and undertook literature review. DM undertook literature review and data analysis. All the authors read and approved the final manuscript.

Author details
[1]International Livestock Research Institute (ILRI), P.O. Box 30709-00100, Nairobi, Kenya. [2]School of Economics, University of Nairobi, P.O. Box 30179-00100, Nairobi, Kenya. [3]School of Economics, Kenyatta University, P.O. Box 43844-00100, Nairobi, Kenya.

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