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Productivity and efficiency analysis of maize under conservation agriculture in Zimbabwe

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ABSTRACT

This study assesses the productivity and efficiency of maize production under conservation agriculture (CA). The analysis is based on a three year (2008–2010) panel sample of small holder farming households across 15 rural districts in Zimbabwe. We make a comparison of CA with alternative conventional farming methods. Our empirical strategy consists of two methods. First, using a fixed effects model, we estimate maize production functions and derive technical change estimates under CA and conventional farming. Second, we estimate a joint stochastic production frontier to compare productivity and technical efficiency between CA and conventional farming. Under CA, technical progress has been land-saving but seed and fertilizer-using, while it has been land-using but seed-saving in conventional farming. Lastly, the results of the efficiency analysis show that that farmers produce 39% more in CA compared with conventional farming, but technical efficiency levels are essentially equal in both technologies. Overall, the results show significant yield gains in CA practices and significant contributions to food production. CA is land-saving, and this is an important issue for land constrained farmers because they can still have viable food production on smaller area. However, high labor and fertilizer demands in CA present some problems in adoption amongst resource-constrained farmers.

1. Introduction

An important challenge in Zimbabwe's smallholder agricultural sector is to raise the productivity of food crop production. In the last decade, the productivity of important staples has declined amongst rural households. For example, maize yields have significantly declined over the years, from about 1500 kg/ha in the early 1990s to around 500 kg/ha after 2000 (Government of Zimbabwe, 2002). Similar to most parts of sub-Saharan Africa, agricultural productivity levels in Zimbabwe have fallen partly due to land degradation as a result of many years of erosive cultivation, and declining soil fertility (Mano, 2006). Increasing frequency of droughts due to growing variability in the climate also presents formidable challenges for crop productivity and overall food security amongst rural households (Mazvimavi, 2011).

A response to declining food production in Zimbabwe has been the wide-scale relief distribution of agricultural inputs to small-scale farmers (Rohrbach et al., 2005; DFID, 2009). As part of these agricultural relief and recovery programs, dissemination of new agricultural technologies has been seen as a strategy to complement input provision and sustain farmers' productivity. Conservation agriculture (CA) is one such technology that has been introduced to small-scale farmers as a more sustainable and productive way of farming. CA is a set of technology principles whose aim is to improve and stabilize crop yields while preserving soil and water, and minimizing the use of some inputs through precision application methods. The three basic principles of CA are: minimum soil disturbance, permanent soil cover, and diversification of crops through rotations (Twomlow et al., 2008; Thierfelder and Wall, 2010).

There have been major investments and a concerted policy drive supporting CA as a way of improving crop productivity in Zimbabwe. According to Andersson and Giller (2012), a significant number of funding agencies, international research and development agencies, and non-governmental organisations (NGOs) have taken a keen interest in promoting CA; not only in Zimbabwe but in other countries in Southern Africa. This growing focus on CA as a policy option for smallholder farmers has also stimulated research interest in evaluating the impact of CA. Specifically, does the use of CA lead to productivity gains and contribute significantly to household food security?

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There is a fast growing empirical literature on the impacts of CA as a technology option in resource-constrained environments in Zimbabwe and other countries in Africa. However, empirical studies have turned in mixed results. Studies by Oduol et al. (2011) and Musara et al. (2012) report that the adoption of CA practices pushes smallholder farmers closer to their production frontier. They also find that an improvement in human capital variables, such as improved access to extension and education, can significantly reduce inefficiencies in production. On the other hand, Giller et al. (2009) report that empirical evidence on CA contributions to yield gains is not clear and inconsistent. Gowing and Palmer (2008), and Nkala et al. (2011) also note that CA may not be an appropriate option for resource-poor farmers due to its high demand for external inputs such as fertilizer and herbicides.

Empirical studies that have been carried out to assess CA impacts in Zimbabwe use different methods and analytical approaches, ranging from on-station and on-farm agronomic experiments to broader socio-economic household surveys (Nyagumbo, 1999; Nkala et al., 2011; Musara et al., 2012). However, most of these studies tend to use cross-sectional data, and do not have a longitudinal dimension. Studies that do use longitudinal data do tend to focus on agronomic impacts such as yield and soil properties, but generally fail to control for household level covariates that may have important interactions in the production process. These data limitations present a challenge in drawing correct inferences and conclusions on the actual contributions of CA. In addition, little is known empirically about the nature of economic relationships, such as technical change, factor productivity, and efficiency under CA technology. For example, higher yields achieved under CA may simply be due to higher input usage but this does not necessarily translate to higher technical efficiency levels (Wouterse, 2010). An analysis of these economic relationships should generate important insights on the effectiveness of CA.

By monitoring farmers who have adopted CA over time, the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) has constructed a panel database, which captures production and socio-economic information of farmers practising CA in 15 districts in Zimbabwe. We make use of this panel data set in this study. Our objective is to contribute to the understanding of CA impacts by utilizing a unique data set that captures maize production under CA and alternative conventional farming practices across different agro-ecological regions. We employ a productivity and efficiency analytical approach and implement econometric methods to estimate factor productivity, technical change and technical efficiency in maize production under CA and draw comparisons with conventional farming practices.

The structure of this article is as follows: in Section 2, we briefly review the literature on CA practices in Africa. Section 3 outlines a theoretical framework for productivity analysis. In Section 4, we specify the empirical models and discuss econometric strategies for estimation. Section 5 describes the data and presents some descriptive analysis. Section 6 reports the major empirical findings from the econometric estimation. We conclude and discuss policy recommendations in Section 7.

2. Literature review

In Zimbabwe, CA is largely practiced by smallholder farmers using small farm implements, such as the hand hoe, to create planting basins. CA technologies typically involve agricultural management practices that prevent the degradation of soil and water resources and thereby permit sustainable farm production without environmental degradation (ECAF, 2002; Haggblade et al., 2004). Mazvimavi (2011) provides a comprehensive review of CA practices in Zimbabwe and other Southern African countries.

Studies have been carried out to assess the effect of CA practises in several African countries. Tsegaye et al. (2008) assess the impacts of CA on land and labor productivity in Ethiopia. Their study analyzes the adoption of the different components of CA and finds that the initial decision to adopt CA is influenced by regional location, family size, access to extension, and formal education. They find a positive relationship between land productivity and the use of CA practices. Hassane et al. (2000) evaluate the impact of planting basins and the use of fertilizer and manure on millet crops in Niger. Their study finds that farmers experienced yield gains of up to 511% between 1991 and 1996. Similarly, significant yield gains are also noted in a planting basins and applied crop residues and fertilizer achieved 56% yield gains in their cotton fields and 100% yield gains in their maize fields.

While there is evidence of CA gains in the literature, there are also studies that present a sharply contrasting assessment of CA impacts. Nyagumbo (1999) reports that the performance of CA relative to existing technologies is highly variable, and dependent on site and farmer characteristics. Gowing and Palmer (2008) examine the evidence of CA benefits amongst small-scale farmers in Africa and conclude that CA does not overcome the constraints found in low external-input systems. They note that CA can deliver the productivity gains required for food security and poverty alleviation targets only if farmers have access to fertilizers and herbicides. They further assert small-scale farmers are not likely to completely adopt CA, but only as a complement to existing management practices. Giller et al. (2009) suggest that the empirical evidence is not clear and inconsistent regarding CA's contribution to yield gains. Their study highlights concerns that include decreasing yields under CA, higher labor requirements when herbicides are not used, a shift of the labor burden to women, and problems with meeting mulching requirements. They also note many cases where the adoption of CA is temporary and only lasts as long as NGOs and research institutions are present, but once the organizations leave, CA is disadopted. Nkala et al. (2011) carry out a meta-analysis of the impacts of CA in Southern Africa and find that CA is better suited for smallholder farmers who can readily access farm implements, financing, and other livelihood assets. Their study concludes that the effectiveness of CA towards improving livelihood outcomes in Southern Africa remains debatable, especially when supportive government policies are lacking. Lastly, Andersson and Giller (2012) note that the appropriateness of CA in highly diverse smallholder farming systems is unclear, and that adoption is only suitable for a limited number of farmers.

Although the studies that have been highlighted above provide key insights, little has been done in the literature to analyze productivity in CA within a longitudinal framework that assesses evidence of technical change in CA relative to conventional farming technologies. In addition, possible differences in the nature of technical progress with respect to input use under CA and conventional farming have not been explored empirically. While evidence of positive productivity impacts under CA have been reported, we do not know whether or not farmers are technically efficient under CA. This paper seeks to contribute to this literature by addressing these gaps. This article will highlight important differences in the contribution of factors of production to technical change in CA relative to conventional farming. In addition, we investigate the efficiency of CA. Together, these results will help to inform best practices and guide policy on technology adoption in small-scale agriculture.

3. Theoretical framework

As a starting point in the analysis of productivity and efficiency of CA, we consider a theoretical framework of Total Factor Productivity (TFP) growth. TFP growth is defined as growth in output that is not explained by a change in inputs. Following this definition and assuming that maize production is not always on the frontier, a change in the productivity of maize can be decomposed into three separate components: (a) movements towards or away from the frontier due to changes in technical efficiency; (b) shifts in the frontier due to the effect of technological innovations or progress; and (c) productivity gains associated with economies of scale (Coelli et al., 2005). We can also incorporate the effects of changes in input allocative efficiency; i.e., a measure of the right mix of inputs in light of the relative price of each input (Kumbhakar and Lovell, 2000). However, this requires data on input prices, which we do not have. Within the scope of our study, TFP growth can be expressed as

$$T\dot{F}P = \Delta TC + \Delta TEC + \Delta SCALE \tag{1}$$

$T\dot{F}P$ is the growth in total factor productivity, ΔTC represents technical change, ΔTEC represents changes in technical efficiency, and $\Delta SCALE$ represents changes in the scale of production. All three components of Eq. (1) are time and producer-specific unless certain parametric restrictions are specified. If maize production technology or technical efficiency is time invariant, then it makes no contribution to productivity growth. Also, the contribution of scale economies depends on the technology being practiced and the data available. Under constant returns to scale, input growth or contraction makes no contribution to productivity growth. Non-constant returns to scale makes a positive contribution to productivity growth if the scale elasticity is greater than one and input use expands, or if the scale elasticity is less than one and input use contracts.

Following the work of Battese and Coelli (1988, 1992, 1995), Farrell (1957), and Kumbhakar and Lovell (2000), we employ stochastic frontier analysis to investigate technical change and technical efficiency of CA. Given a production technology where a single output y is produced from a vector of inputs $\boldsymbol{x}$ at time t, we say that technical progress occurs between periods t and $t+1$ when the production possibility set expands from (x^t, y^t) to (x^{t+1}, y^{t+1}) where $f(x, t+1; \beta) > f(x, t; \beta)$. Production is technically inefficient in both periods, if $y^t < f(x^t, t; \beta)$ and $y^{t+1} < f(x^{t+1}, t+1; \beta)$, and technical efficiency improves from period t to period $t+1$, if $\frac{y^t}{f(x^t,t;\beta)} < \frac{y^{t+1}}{f(x^{t+1},t+1;\beta)}$. Productivity growth occurs, if $\frac{y^{t+1}}{x^{t+1}} > \frac{y^t}{x^t}$. To estimate productivity growth, we assume a stochastic frontier production function in the format:

$$y_{it} = f(x_{it}, t; \beta) \cdot \exp(-u_{it}), \tag{2}$$

where y_{it} is the output of the ith producer ($i = 1, \ldots, N$) in the tth period ($t = 1, \ldots, T$), $f(x_{it}, t; \beta)$ is the production frontier with technology parameter vector β to be estimated, $x = (x_1, \ldots, x_N) \geqslant 0$, as mentioned, is an input vector, t is a time trend serving as a proxy for technical change, and $u_{it} \geqslant 0$ represents output-oriented technical inefficiency, which is the ratio of observed output to maximum feasible output. For this technology, the production frontier provides the upper boundary of production possibility sets. The input–output combination of each producer is located on or beneath the production frontier. Totally differentiating the production frontier $f(x_{it}, t; \beta)$ with respect to time yields:

$$\frac{d\ln f(x_{it}, t; \beta)}{dt} = \frac{d\ln f(x_{it}, t; \beta)}{dt} + \sum_j \frac{d\ln f(x_{it}, t; \beta)}{dx_{jit}} \frac{dx_{jit}}{dt}. \tag{3}$$

The first and second terms on the right-hand side of Eq. (3) measure the change in frontier output caused by technical change and change in input use, respectively. From the output elasticity of input j, $\varepsilon_j = \partial \ln f(\cdot)/\partial \ln x_j$, the second term can be expressed as $\sum_j \varepsilon_j \dot{x}_j$, where a dot over a variable indicates its rate of change with respect to time. Thus, Eq. (3) can be rewritten as

$$\frac{d\ln f(x_{it}, t; \beta)}{dt} = TC_{it} + \sum_j \varepsilon_j \dot{x}_{jit}. \tag{4}$$

The overall productivity change is not only affected by the technical change (TC), but also by the change in technical efficiency, $TEC = -\frac{du}{dt}$. Technical change is positive if exogenous technical change shifts the production frontier upward for a given level of inputs. When TC is negative, the production frontier is shifted downward. If du/dt is negative, technical efficiency improves over time, and $-du/dt$ can be interpreted as the rate at which an inefficient producer catches up to the production frontier.

Given this theoretical framework, and the data that we have, we can develop empirical models that allow us assess productivity of CA technology. We are interested in measuring technical change, factor productivity, and efficiency under the two different technology regimes.

4. Empirical strategy

This study estimates a stochastic production frontier to investigate productivity and technical efficiency. While there are deterministic methods (e.g., data envelopment analysis), these assume that all distributions are attributable to inefficiency. In agriculture, however, this assumption is quite restrictive since stochastic factors such as rainfall and pests can have a large effect on the final outcome. Therefore, we use a joint frontier, with a specific interest in comparing efficiency levels in CA and conventional farming. Observations from the two technologies are pooled so that technical efficiency predictions are derived from the same data, as suggested by Battese et al. (2004).

4.1. Empirical specification

We estimate a stochastic frontier model using a translog functional form. Specifically, we estimate the following:

$$\ln y_{it} = \alpha_{i0} + \sum_j^J \beta_j \ln x_{jit} + \frac{1}{2}\sum_j^J \sum_k^J \beta_{jk} \ln x_{jit} \ln x_{kit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_j^J \beta_{jt} \ln x_{jit} t + \beta_{it} A_{it} + v_{it} - u_{it}, \tag{5}$$

where y_{it} is output produced, subscript $i = 1, 2, \ldots, N$ denotes households, $t = 1, 2, \ldots, T$ are time periods, and $j, k = 1, 2, \ldots, J$ are the inputs used, represented by vector $\boldsymbol{x}$ in farm production. The error term is composed of two independent elements: $v_{it} \sim \text{iid } N(0, \sigma_v^2)$ is the random noise error component and $u_{it} \geqslant 0$ is the technical inefficiency error component. A dummy variable A_{it} is included in the model to identify the difference in production levels between CA and conventional farming. The constant term α_{i0} controls for unobserved factors that vary across households but are time-invariant, such as soil quality.

Following the stochastic production frontier model in Eq. (5), we assume that the inefficiency effects are independently distributed and μ_{it} arises by truncation at zero of the normal distribution (Kumbhakar and Lovell, 2000) with mean μ_t, and variance, σ_u^2, where μ_t is defined by

Table 1
Study sample showing number of households practicing conservation agriculture and conventional farming. *Source:* ICRISAT Conservation Agriculture panel data 2008–2010.

Technology	Number of households				Observations	
	2008	2009	2010	Mean	Total	Percentage
Conservation agriculture	265	291	200	252	756	53.62
Conventional farming	155	270	229	218	654	46.38
Total					1410	100
Both technologies	137	197	133	156	467	49.52
Conservation agriculture only	128	94	67	96	289	30.65
Conventional farming only	18	73	96	62	187	19.83
Total	283	364	296	314		100

$$\mu_t = \delta_0 + \sum_{m=1}^{M} \delta_m Z_{mt} + \delta_t t, \qquad (6)$$

Z_{mt} is a vector of farm specific inefficiency related variables ($m = 1,\ldots,M$), at time t, and δ_m is a vector of unknown parameters to be estimated. Technical efficiency is assumed to be time varying. Since the dependent variable μ_t in the inefficiency model is a measure of inefficiency, a positive sign on a parameter indicates a negative efficiency effect. In our estimation of the stochastic frontier, we employ a one stage approach that uses maximum likelihood to estimate the production function for $\ln y_{it}$ simultaneously with the inefficiency effects model for μ_t. We use the econometric software package LIMDEP to estimate the stochastic frontier.

4.2. Model variables

The dependent variable used in the stochastic frontier analysis is the logarithm of quantity of maize harvested, in kilograms (kg), by a household. If a household has more than one maize plot under the same technology, then quantity harvested is total harvest from all maize plots under the same technology. The input quantities are also aggregates of inputs used in different plots under the same technology. Our data do not permit us to do a plot specific analysis across the panel period. Hence, for each household, and for respective technologies, we aggregate the data from individual plots. The variables for the direct factors of production are land (A), labor (L), draft animals (K), fertilizer (F), and seed (S). Land is total cultivated area in hectares. Labor is total farm labor available in the household, expressed in male adult equivalent units. Draft animals are mainly used in conventional farming for land preparation. In our sample, land preparation in conservation agriculture plots is accomplished by hand hoes. However, we do not rule out interactions of draft input in the production process under CA, for example for some weeding methods. So draft ownership is included as a direct factor of production in both CA and conventional farming. Fertilizer is the total amount of fertilizer applied in kg. Seed is the total quantity of seed planted in kg. A time variable is included to account for disembodied technical change.

To measure differences in maize productivity between CA and conventional farming, we include a technology dummy (1 = CA, 0 = conventional farming). The technology dummy variable is specific to output observations from CA and conventional farming. For example, if, for a given year, a household practiced both CA and conventional farming, the household has 2 output observations in the data set. The output observation under CA has the technology dummy variable taking a value of 1, whereas the observation for conventional farming has the technology dummy variable taking a value of zero. We also control for rainfall region by including a dummy variable that equals 1 if it is a high rainfall area (agro-ecological regions II and II or those with greater than 650 mm of rainfall per annum), and 0 for low rainfall area (agro-ecological region IV and V, or those with fewer than 650 mm of rainfall per annum).

In the efficiency model, we hypothesize that household socio-economic factors, type of technology, and some direct factors of production will affect technical efficiency. The variables used in the efficiency model include: gender (dummy variable taking the value of 1 if it is a male-headed household, zero otherwise), age and education of the household head, and asset endowments, which are expressed as an index that captures the household's ownership and access to farming implements – e.g., ploughs, cultivators, hoes. A time variable is included to estimate the effect of time on technical efficiency. Land and labor are also included in the efficiency model. Lastly, we include the technology dummy variable (described earlier), to capture whether inefficiency varies by technology.

Table 2
Summary statistics of variables used in analysis of maize production. *Source:* ICRISAT Conservation Agriculture panel data 2008–2010.

Technology	Production variables							Efficiency variables			
	Year	Maize (kgs)	Area (ha)	Labor (male adult)	Draft (number of cattle)	Seed (kgs)	Fertilizer (kgs)	Gender (male = 1, female = 0)	Age of head	Education (years of head)	Physical asset index
Conservation agriculture	2008	362.40	0.36	3.69	0.74	8.05	35.46	0.63	50.48	6.50	72.98
	2009	484.25	0.36	3.66	0.62	9.19	33.84	0.68	55.79	6.53	97.04
	2010	501.69	0.37	2.54	1.24	9.13	53.53	0.59	54.03	6.91	287.95
	Average	449.45	0.36	3.30	0.87	8.79	40.94	0.63	53.43	6.65	152.66
Conventional farming	2008	325.09	0.94	3.84	0.90	19.27	38.68	0.63	50.75	6.57	84.00
	2009	575.07	0.75	2.93	0.64	17.20	33.52	0.69	54.53	6.79	91.74
	2010	649.29	0.85	2.63	1.39	19.03	62.64	0.65	54.21	6.81	356.20
	Average	516.48	0.85	3.14	0.98	18.50	44.95	0.66	53.16	6.73	177.31
Both technologies	2008	348.63	0.57	3.74	0.80	12.19	36.65	0.63	50.58	6.53	77.05
	2009	527.96	0.55	3.31	0.63	13.05	33.69	0.69	55.20	6.65	94.49
	2010	580.48	0.63	2.59	1.32	14.42	58.39	0.62	54.13	6.86	324.38
	Average	485.69	0.58	3.21	0.92	13.22	42.91	0.65	53.30	6.68	165.31

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Table 3
Quantity of inputs and output for maize production. *Source:* ICRISAT Conservation Agriculture panel data 2008–2010.

Technology	Year	Land (ha)	Fertilizer (kg/ha)	Seed (kg/ha)	Maize yield (kg/ha)
Conservation agriculture	2008	0.36	143.68	33.23	1474.80
	2009	0.36	142.09	37.71	1747.56
	2010	0.37	187.52	29.79	1607.37
	Average	0.36	154.66	34.04	1614.86
Conventional	2008	0.94	85.14	29.53	517.34
	2009	0.75	68.94	33.44	1070.37
	2010	0.85	97.26	25.33	857.02
	Average	0.85	82.69	29.67	864.60
Both technologies	2008	0.57	122.07	31.86	1121.45
	2009	0.55	106.88	35.66	1421.64
	2010	0.63	139.34	27.41	1206.83
	Average	0.58	121.28	32.02	1266.87

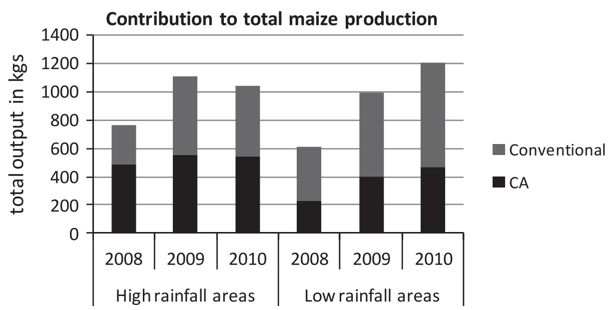

Fig. 1a. Output shares for alternative technologies (all households).

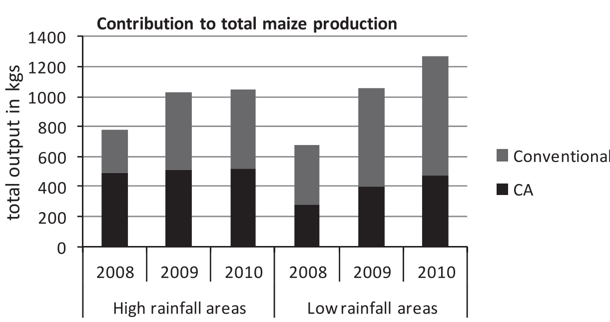

Fig. 1b. Output shares for alternative technologies (households practicing both technologies).

4.3. Factor productivity and technical change

Our interest here is in exploring differences in technical change and factor productivity between CA and conventional farming. Note that, we do not use a stochastic frontier model. This is because, in this section, we are primarily interested in comparing factor productivity between the two technologies, not the efficiency levels. However, to make this comparison, we do not use a joint model for the two technologies, as in the efficiency analysis. Doing so would require us to introduce interaction terms for all input variables with the technology dummy variable, but this would result in too many variables, and possibly create problems of multi-collinearity. Instead, we estimate separate maize production functions for CA and conventional farming using fixed effects panel regression. The availability of panel data makes it possible to control for individual household specific effects. The decision lies between choosing a fixed effects and random effects models. We run a statistical test to choose the appropriate panel model specification (Appendix A). In the panel specification test, we use a Cobb–Douglas functional form and the more flexible translog functional form. In both specifications, the test results favor a fixed effects approach. We choose the translog as our preferred functional form as suggested by the results of a likelihood ratio test (Appendix B).

The production functions we estimate are:

$$\ln y_{it} = \alpha_{i0} + \sum_{j}^{J} \beta_j \ln x_{jit} + \frac{1}{2}\sum_{j}^{J}\sum_{k}^{J} \beta_{jk} \ln x_{jit} \ln x_{kit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_{j}^{J} \beta_{jt} \ln x_{jit} t + e_{it}. \quad (7)$$

The notation is the same as for Eq. (5), except that the error term e_{it} is normally distributed, and there is no technology dummy since we run separate regressions. Technical change is neutral with respect to inputs if $\beta_{jt} = 0\ j$, and absent if $\beta_t = \beta_{tt} = \beta_{jt} = 0\ j$. We are interested in identifying whether there are differences in the nature of technical progress with respect to input use under the two technologies.

5. Data and descriptive analysis

This study uses ICRISAT panel data from household surveys collected between 2008 and 2010 in 15 rural districts in Zimbabwe. By observing the same farmers in successive seasons

Table 4
Comparison of efficiency levels between conservation agriculture and conventional farming using input–output ratios.

Year	Area		Labor		Draft		Seed		Fertilizer	
	CA	Conv.	CA	Conv.	CA	Conv.	CA	Conv.	CA	Conv.
2008	0.002***	0.005	0.023*	0.027	0.013	0.011	0.046***	0.111	0.189***	0.264
2009	0.001***	0.002	0.017***	0.012	0.007	0.006	0.029***	0.049	0.116	0.123
2010	0.002***	0.003	0.014	0.014	0.012	0.011	0.040***	0.073	0.230	0.225
Average	0.002***	0.003	0.018	0.016	0.011	0.009	0.037***	0.072	0.174	0.201

Notes: T-tests for equality of means of input output ratios are done. The significance levels compare CA and conventional farming input output ratios.
* Significance levels indicated for 10% significance.
*** Significance levels indicated for 1% significance.

Table 5
Results of fixed effects regressions of Translog production functions.

Conservation agriculture fixed effects regression				Conventional farming fixed effects regression			
Variable		Coefficient	Standard error	Variable		Coefficient	Standard error
Land	β_A	−0.307	0.254	Land	β_A	0.956*	0.534
Labor	β_L	0.739**	0.337	Labor	β_L	−0.651	0.621
Draft Animal	β_K	−1.023**	0.488	Draft Animal	β_K	2.292***	0.741
Seed	β_S	0.008	0.305	Seed	β_S	−0.532	0.741
Fertilizer	β_F	0.338**	0.138	Fertilizer	β_F	−0.081	0.184
Land * Land	β_{AA}	0.068	0.084	Land * Land	β_{AA}	0.097	0.114
Labor * Labor	β_{LL}	−0.124	0.138	Labor * Labor	β_{LL}	0.203	0.176
Draft * Draft	β_{KK}	0.205	0.348	Draft * Draft	β_{KK}	0.896***	0.285
Seed * Seed	β_{SS}	0.294***	0.091	Seed * Seed	β_{SS}	0.169	0.227
Fertilizer * Fertilizer	β_{FF}	0.022	0.028	Fertilizer * Fertilizer	β_{FF}	0.168***	0.031
Land * Labor	β_{AL}	0.170*	0.088	Land * Labor	β_{AL}	−0.082	0.157
Land * Draft	β_{AK}	−0.131	0.097	Land * Draft	β_{AK}	0.766***	0.162
Land * Seed	β_{AS}	−0.137*	0.081	Land * Seed	β_{AS}	−0.171	0.131
Land * Fertilizer	β_{AF}	0.062**	0.031	Land * Fertilizer	β_{AF}	0.055	0.043
Labor * Draft	β_{LK}	0.127	0.109	Labor * Draft	β_{LK}	−0.468**	0.191
Labor * Seed	β_{LF}	−0.172	0.098	Labor * Seed	β_{LF}	0.001	0.166
Labor * Fertilizer	β_{LS}	0.026	0.036	Labor * Fertilizer	β_{LS}	0.079*	0.042
Draft * Seed	β_{KS}	0.106	0.134	Draft * Seed	β_{KS}	−0.695	0.202
Draft * Fertilizer	β_{KF}	0.060	0.060	Draft * Fertilizer	β_{KF}	−0.088**	0.044
Seed * Fertilizer	β_{SF}	−0.026	0.042	Seed * Fertilizer	β_{SF}	−0.118**	0.051
Land * Time	β_{AT}	0.296***	0.062	Land * Time	β_{AT}	−0.173*	0.098
Labor * Time	β_{LT}	−0.072	0.060	Labor * Time	β_{LT}	0.040	0.090
Draft * Time	β_{KT}	0.096	0.067	Draft * Time	β_{KT}	−0.096	0.085
Seed * Time	β_{ST}	−0.155**	0.069	Seed * Time	β_{ST}	0.259**	0.105
Fertilizer * Time	β_{FT}	−0.111***	0.031	Fertilizer * Time	β_{FT}	0.022	0.025
Time	β_T	2.312***	0.321	Time	β_T	1.183**	0.464
Time^2	β_{TT}	−0.615***	0.100	Time^2	β_{TT}	−0.927***	0.129
Draft access	β_{DD}	0.135	0.125	Draft access	β_{DD}	0.310**	0.133
Rainfall region	β_R	−0.231***	0.078	Rainfall region	β_R	−0.211**	0.093
Observations		756				654	
Households		392				405	
R-squared		0.800				0.860	
Adj *R*-squared		0.548				0.583	

* Statistical significance for the 10% significance level.
** Statistical significance for the 5% significance level.
*** Statistical significance for the 1% significance level.

of real CA practice in a non-experimental setting, it is possible to compare CA and conventional farming practices within the same households. Since we are primarily interested in the effects of CA on maize production, we omit observations where no maize is produced (e.g. due to drought). As a result, we exclude approximately 14% of the data. Whenever a sub-sample of the data is used, there is always a concern of sample bias. We estimate a Heckman selection model to check for sample selection bias. The test result suggests that there is no sample selection bias (Appendix C). In addition, during the study period, there was some attrition as several households could not be re-interviewed in successive waves of the survey. Consequently, the panel is un-balanced. A possible strategy is to account for attrition by using dynamic panel data models, but this is not the focus of the paper.

Table 1 shows the average number of households and total observations. The total number of observations from CA and conventional farming equals 1410 for the entire panel period. This number of observations is based on a total of 470 different households interviewed during the three year panel period. In our sample, there are some overlaps in the technologies being practiced. On average, across the three years panel period, about 50% the households practice both CA and conventional farming. Fewer households specialize in just one type of technology i.e. about 30% of households only practice CA, and approximately 20% only practice conventional farming. The average number of households interviewed in each panel period is 314.

Table 2 gives some descriptive statistics of the production variables and factors hypothesized to explain productivity and technical efficiency in maize production. These are elaborated further in the next section, which gives a descriptive analysis of maize productivity under CA and conventional farming.

Table 3 shows land allocation in hectares, where on average plots under conventional farming are significantly larger: 0.85 ha compared to 0.35 ha for CA. The most likely reason for this large difference is that farmers are more likely to allocate a larger share of their land to the familiar technology, especially when the existing technology is relatively easier to implement on larger tracts of land. CA is generally implemented on smaller tracts of land due to labor constraints in digging planting basins, where handheld hoes are typically used. Fertilizer application rates are significantly higher on CA plots, with 155 kg/ha being compared with 83 kg/ha on the conventional plots. This is likely due to the fact that fertilizer subsidies are available for CA plots. Seed application rates are higher in CA, and this is due to planting recommendations that encourage using more seed per planting station. In terms of general input use, CA is not necessarily associated with conservative input levels. The conservation attributes of CA are mainly realized through the agronomic aspects, such as conserving soil structure, improving soil moisture through the use of mulch, and the precision application of inputs.

Fig. 1a shows that in both high and low rainfall areas, CA output share is quite high, even though CA is implemented on only 0.36 ha of land compared to 0.85 ha for conventional farming, on average. In high rainfall areas, CA contributes on average 53.59% of the total output. In low rainfall areas, the share of output from CA is 37.60%. However, since some households do not practice CA, we go a step further in our analysis of output shares and limit the sample to households practicing both technologies (Fig. 1b). We find that the output shares remain very similar. In high rainfall areas, CA contributes on average 53.19% of total output. In low rainfall areas, the share of output from CA is 38.12%. These findings strongly indicate that CA technology, although implemented on smaller plots, still contributes significantly to food production, in both high and low rainfall areas.

The last descriptive statistic we calculate is a partial productivity index, which is the ratio of input use to output produced. These input–output (IO) ratios allow for comparison of factor productivity where lower IO ratios indicate higher factor productivity. Table 4 shows the mean differences in IO ratios between CA and conventional farming. In every year, CA has higher factor productivity for all the inputs except draft. CA technology by design avoids the use of draft as a coping strategy for households with no draft animals. These households can carry out land preparation and plant on time without having to wait to borrow draft animals from neighbors. Fertilizer productivity is only significantly higher for CA in 2008. Not surprisingly, the significantly higher fertilizer regimes on CA do not yield correspondingly higher productivity for this factor. A common concern with subsidized inputs is that they can be overused as their marginal cost is artificially lower, which leads to their being used at the point where the marginal productivity is not as high as it would be otherwise (i.e., if the mar-

Table 6
Joint stochastic production frontier estimates for maize production.

Translog stochastic frontier model				Inefficiency effects model			
Variable		Coefficient	Standard error	Variable		Coefficient	Standard error
Constant	β_0	2.855^{***}	0.497	Age	γ_{AG}	−0.003	0.013
Land	β_A	−0.076	0.188	Education	γ_E	0.000	0.086
Labor	β_L	0.665^{***}	0.2255	Gender	γ_G	−0.001	0.632
Draft Animal	β_K	0.236	0.299	Physical assets	γ_{AV}	-0.003^{*}	0.001
Seed	β_S	0.320	0.233	Draft	γ_D	0.430	0.628
Fertilizer	β_F	0.05	0.078	Time	γ_T	-4.383^{***}	1.654
Land * Land	β_{AA}	0.059	0.054	Time * Time	γ_{TT}	1.389^{***}	0.470
Labor * Labor	β_{LL}	0.055	0.093	Area	γ_A	1.404^{***}	0.380
Draft * Draft	β_{KK}	0.229	0.135	Labor	γ_L	0.263	0.571
Seed * Seed	β_{SS}	0.078	0.079	Region	γ_R	0.009	0.570
Fertilizer * Fertilizer	β_{FF}	0.090^{***}	0.015	Technology	γ_{TC}	0.416	0.730
Land * Labor	β_{AL}	0.185^{***}	0.062				
Land * Draft	β_{AK}	0.143^{**}	0.079				
Land * Seed	β_{AS}	0.023	0.056				
Land * Fertilizer	β_{AF}	0.003	0.021				
Labor * Draft	β_{LK}	−0.028	0.069				
Labor * Seed	β_{LF}	-0.196^{***}	0.069				
Labor * Fertilizer	β_{LS}	0.005	0.021				
Draft * Seed	β_{KS}	−0.112	0.081				
Draft * Fertilizer	β_{KF}	0.049^{**}	0.021				
Seed * Fertilizer	β_{SF}	-0.057^{**}	0.023				
Land * Time	β_{AT}	0.132^{***}	0.038				
Labor * Time	β_{LT}	−0.017	0.047				
Draft * Time	β_{KT}	−0.043	0.050				
Seed * Time	β_{ST}	0.073	0.045				
Fertilizer * Time	β_{FT}	−0.011	0.014				
Time	β_T	1.394^{***}	0.231				
Time^2	β_{TT}	-0.573^{***}	0.091				
Draft access	β_{DD}	0.244^{***}	0.057				
Rainfall region	β_R	0.001	0.040				
CA technology	β_T	0.394^{***}	0.048				
λ		1.916	0.735				
Sigma u		1.232	0.337				
$\sigma^2 v$		0.413					
$\sigma^2 u$		1.517					
Likelihood ratio		−1549.7					
Observations		1410					
Households		470					

* Statistical significance for the 10% significance level.
** Statistical significance for the 5% significance level.
*** Statistical significance for the 1% significance level.

Table 7
Distribution of efficiency scores derived from Stochastic production frontier estimates for maize production (percentage of households).

Technology	Year	Percentage of households in efficiency score category					N
		<0.40	0.41–0.60	0.61–0.80	>0.80	Average	
Conservation agriculture	2008	1.89	21.13	60.00	16.98	0.681	265
	2009	0.69	19.59	64.60	15.12	0.684	291
	2010	1.00	22.50	59.00	17.50	0.687	200
	Average	1.19	21.07	61.20	16.53	0.684	252
Conventional farming	2008	1.29	24.52	63.87	10.32	0.664	155
	2009	0.76	19.70	65.53	14.02	0.684	264
	2010	2.18	21.40	58.08	18.34	0.677	229
	Average	1.41	21.87	62.49	14.23	0.677	216

ket price had been paid). While these productivity indices are useful, it is important to note that they are limited in terms of how accurately and comprehensively they portray overall productivity, and can be misleading when considered in isolation (Kalirajan and Wu, 1999). The subsequent sections of the paper discuss more complete measures of productivity.

6. Empirical results

Table 5 presents results from the fixed effects regressions under CA and conventional farming. Under CA, labor has a positive and statistically significant effect on yield. Strangely, the use of draft animals has a negative and statistically significant effect. This unexpected result may be because in years of poor output, farmers may be using more draft inputs to control for weeds (Battese and Coelli, 1992). The coefficients on land and seed are not statistically significant. The models include a time variable to account for technical change, and a quadratic time variable that allows for non-monotonic technical change (Coelli et al., 2005). There is evidence of technical progress in CA (46% on average) for the three year panel period. The coefficient on time-squared is negative and statistically significant, which indicates that the rate of technical change has been increasing at a decreasing rate. Time is also interacted with each (logged) input variable to allow for non-neutral technical change. In the CA model, the positive coefficient of time interacted with land implies that technical change has been land saving under CA. Time interactions with draft and labor have no significant effects under CA. This implies that technical change is neutral with respect to these inputs. However, overall technical change is not neutral because some production factors significantly change over time. The coefficients of time interactions with seed and fertilizer are negative (and significant) implying factor using technical change for these inputs.

Under conventional farming, the coefficients on land and draft animals are both positive and statistically significant, while the coefficients for labor, seed and fertilizer are not statistically different from zero. These results suggest that draft animals contribute to yields under conventional farming, in contrast to CA, but this may be because draft animals are the dominant form of land preparation under conventional farming but used only sparingly (possibly only when conditions are most dire) in the case of CA. The coefficient on time is positive and statistically significant, which suggests evidence of technical progress. The time-squared coefficient is particularly large and suggests that technical progress in recent years has greatly slowed down. Looking at the time and input interaction coefficients reveals that technical change has been land using and seed saving. Coefficients on labor, draft, and fertilizer are not significant, implying technical neutrality with respect to these inputs.

Table 6 presents the results of the stochastic frontier model. The key result here is the coefficient on the technology dummy (CA technology). This result suggests that, holding all other factors constant, a farmer produces 39% more maize per unit of land under CA than conventional farming. This result is statistically significant at the 1% level, and consistent with empirical findings from other studies, where different forms of soil and water conservation technologies are reported to be associated with significant yield gains compared to traditional methods.

We also present the results from the inefficiency model in Table 6. Technical efficiency scores are estimated and simultaneously used in the inefficiency model. In the inefficiency model, a positive sign indicates that the variable increases inefficiency. The results show that technical efficiency is not affected by the type of technology that farmers use (the technology coefficient is not statistically significant). Demographic factors (gender, education, labor availability) also have no effect on inefficiency. Households with higher physical asset levels are more efficient. This seems plausible given that higher asset values imply greater availability of farming implements-which translates to more timely and effective farming operations. Our results also show that farmers operating on relatively large tracts of land are likely to be less efficient. This is characteristic of the production environment where inputs are limited; hence increasing land while holding other direct factors (such as draft and labor) constant will lead to inefficiency in production. Lastly, farmer efficiency is increasing over time, but at a decreasing rate.

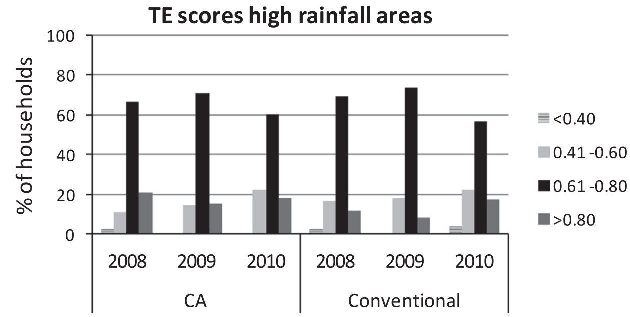

Fig. 2a. Technical efficiency scores in high rainfall regions.

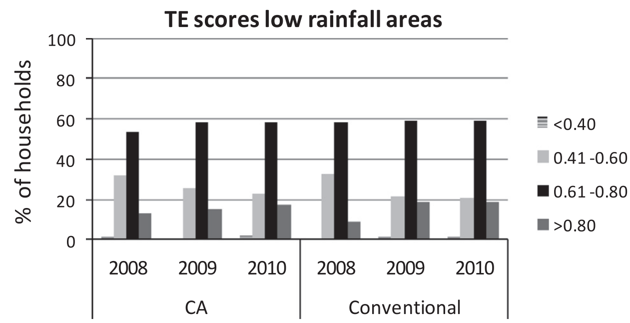

Fig. 2b. Technical efficiency in low rainfall regions.

Technical efficiency scores are reported in Table 7. Average efficiency levels in both high and low rainfall areas are not statistically different between CA and conventional farming. Fewer than 25% of households have average efficiency scores below 60%. The majority of households (62% under both technologies) have average efficiency scores in the range of 61–80%. In CA about 16.5% of households achieve technical efficiency levels greater than 80% while 14% of households achieve the same range in conventional farming. Figs. 2a and 2b show the efficiency levels for the alternative technologies in high and low rainfall areas, respectively. On average for CA plots, the level of efficiency is 70% and 68% in high and low rainfall areas, respectively. Conventional plots achieve 68% efficiency regardless of rainfall area. Technical efficiency tends to vary more in high rainfall areas compared to low rainfall areas under both technologies. Again, the efficiency levels remain the same for both technologies. Although the fixed effects regressions showed that factor productivity is strikingly different between CA and conventional farming, it's interesting to note that technical efficiency levels between the two technologies are very similar. The higher yield in CA does not translate into higher efficiency.

7. Conclusion and discussion

CA technology is implemented in relatively smaller plots than conventional farming. However, there is evidence of significant contribution of CA technology to total maize production amongst households. Our results show that productivity is greater in CA for all inputs except draft. There is also evidence of technical progress in CA for the three year panel period. Technical progress has been land-saving but seed and fertilizer-using in CA, while land-using and seed-saving in conventional farming. Joint frontier estimates indicate greater productivity gains in CA (39% more than conventional farming-ceteris paribus). Although CA is associated with higher yields, technical efficiency levels are generally the same for both technologies. The majority of farmers achieve efficiency scores in the 60–80% range under both technologies.

Interesting policy insights can be drawn from these results. First, it is clear that CA results in significant yield gains and significant contributions to food production although it is implemented on small pieces of land. CA is land saving, and this is an important issue for land constrained farmers because they can still have viable food production with limited land. On the other hand, high labor demands in CA present some problems in adoption. NGOs that promote CA commonly target vulnerable farmers, such as women, the elderly, and households affected by HIV/AIDS. NGO targeting of vulnerable households may impact negatively on labor availability for CA practices. Hence there is a need to include better resourced farmers as technology innovators.

CA requires higher quantities of seed and fertilizer. These inputs are not readily available to most small holder farmers hence adoption may be stalled by that fact. However, there are opportunities to counter this problem if CA farmers can achieve a marketed surplus, which can generate money to buy the seed and fertilizer. It is therefore important for functional output markets to be in place to complement technology adoption.

Some limitations to this study include the short panel period, which limits observing long-term trends. The unavailability of price information also prevents us from doing a more complete economic analysis. It would also be interesting to look at adoption intensity, in terms of what components of CA are being practiced more and how adoption levels are related to efficiency and productivity gains.

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Appendix A

Table A.1
Panel regressions to test fixed effects versus random effects.

OLS translog model			
Variables		Coefficient	Standard error
Constant	β_0	2.200***	0.583
Land	β_A	−0.209	0.217
Labor	β_L	0.464**	0.275
Draft Animal	β_K	0.440	0.370
Seed	β_S	0.390	0.261
Fertilizer	β_F	0.083	0.094
Land * Land	β_{AA}	−0.010	0.057
Labor * Labor	β_{LL}	0.002	0.096
Draft * Draft	β_{KK}	0.210	0.172
Seed * Seed	β_{SS}	0.058	0.082
Fertilizer * Fertilizer	β_{FF}	0.091***	0.018
Land * Labor	β_{AL}	0.127**	0.065
Land * Draft	β_{AK}	0.163**	0.084
Land * Seed	β_{AS}	0.028	0.057
Land * Fertilizer	β_{AF}	0.029	0.022
Labor * Draft	β_{LK}	−0.020	0.091
Labor * Seed	β_{LF}	−0.139**	0.078
Labor * Fertilizer	β_{LS}	0.010	0.024
Draft * Seed	β_{KS}	−0.165**	0.089
Draft * Fertilizer	β_{KF}	0.034	0.027
Seed * Fertilizer	β_{SF}	−0.058**	0.026
Land * Time	β_{AT}	0.086**	0.048
Labor * Time	β_{LT}	−0.011	0.055
Draft * Time	β_{KT}	−0.046	0.058
Seed * Time	β_{ST}	0.056	0.056
Fertilizer * Time	β_{FT}	−0.005	0.018
Time	β_T	1.809***	0.257
Time * Time	β_{TT}	−0.852***	0.086
Draft access	β_{DD}	0.182***	0.067
Region	β_R	−0.012	0.047
CA technology	β_{RT}	0.336***	0.046
R^2		0.427	
Huasman p value		0.000	
Observations		1410	
Households		470	

OLS Cobb Douglas			
Variables		Coefficient	Standard error
Constant	γ_0	2.682***	0.208
Land	γ_A	0.298***	0.041
Labor	γ_L	−0.012	0.054
Draft Animal	γ_K	−0.001	0.084
Seed	γ_S	0.273***	0.049
Fertilizer	γ_F	0.145***	0.016
Draft	γ_D	0.163**	0.087
Time	γ_T	1.622***	0.262
Time * Time	γ_{TT}	−0.377***	0.066
Region	γ_R	0.074	0.056
CA technology	γ_{RT}	0.301***	0.057
R^2		0.634	
Huasman p value		0.098	
Observations		1470	
Households		470	

Significant Hausman p-value indicates that the fixed effects model is preferred to the random effects.
* Statistical significance for the 10% significance level.
** Statistical significance for the 5% significance level.
*** Statistical significance for the 1% significance level.

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Appendix B

In the literature, the translog has commonly been preferred as a more flexible functional form that allows for interaction of inputs, unlike the Cobb Douglas which does not allow for input interactions and assumes elasticity of substitution between inputs equals one. To tests for functional forms a likelihood ratio (LR) tests is used. The LR test is only valid for nested models. The LR test statistic is $\lambda = -2[L(H_0) - L(H_1)]$, where $L(H_0)$ and $L(H_1)$ are the values of the log-likelihood function under the specifications of the null and alternative hypotheses, H_0 and H_1, respectively. If the null hypothesis is true, then λ has approximately a Chi-square (or mixed Chi-square) distribution with degrees of freedom equal to the number of restrictions. The assumption that the maize production in this sample follows Cobb–Douglas estimations ($\beta_{jk} = 0,\ \forall j,\ k$ and $\beta_{jt} = 0\ \ \forall j,\ t$) are strongly rejected at 1 percent significance level (Chi calculated = 63.691, with 35df).

Table C.1
Heckman sample selection model.

Probit model of participation in sample			OLS corrected regression for the selected sample		
Variable	Coefficient	Standard error	Variable	Coefficient	Standard error
Constant	−1.33207***	0.63128	Constant	2.5282***	0.321265
Area	0.4585***	0.062441	Area	0.31377***	0.050756
Labor	0.061906	0.117707	Labor	0.059642	0.041665
Daft access	0.12438	0.130738	Draft	0.137109	0.054606
Time	3.391665***	0.779112	Seed	0.327514***	0.04257
Time * Time	−0.86496***	0.194115	Fertilizer	0.146021***	0.013163
Region	0.201059	0.129679	Draft access	0.140083**	0.057376
Benefit	0.228885*	0.139119	Time	2.085827***	0.31167
			Time * Time	−0.48684***	0.079125
			Region	0.040619	0.04845
			CA technology	0.336713***	0.052969
			σ (1)	0.797177***	0.023915
			Rho(1,2)	0.249532	0.351051
			Log likelihood	−2206.438	
			N total sample	1635	
			N selected sample	1410	

* Statistical significance for the 10% significance level.
** Statistical significance for the 5% significance level.
*** Statistical significance for the 1% significance level.

Appendix C

C.1. Sample selection

There are instances in the survey data set were households did not produce maize in a particular year. These observations were excluded from the analysis carried out in the study. An average of about 13.8% of observations were excluded from the analysis A concern that might arise is that of sample selection bias. If the excluded farmers had particular characteristics specific to them and not observed in the included sample (e.g. non beneficiaries are likely to be less vulnerable households), then the sample used for analysis would not be random but rather biased. Households that did not receive input subsidies were more likely to be excluded from the sample. The full sample consisted of 1635 observations and the proportion of households that were non beneficiaries[1] (of input subsidies) in this sample is 20.6%. In the selected sample, about 20% of non beneficiaries were excluded, compared to 11% of beneficiaries being excluded. To explore the potential problem of sample selection bias, a Heckman's sample selection model is implemented. In the model the probability of being a maize producer for a particular year is modeled as a function of whether or not a household received input subsidies (dummy variable taking the value 1 if beneficiary and 0 otherwise). An assumption is made that receiving input subsidies will have an effect on whether a household produced or not, but will not have a direct effect on levels of production. Within reason, this assumption seems plausible.

The results of the model are presented in Table A.1. The probit model for participation in the sample indicates that there is a greater probability for participation if a household is a beneficiary (coefficient on beneficiary is positive and statistically significant).

To evaluate if there is sample selection bias, we look at the rho (1,2) coefficient in the corrected model. The rho (1,2) coefficient is not statistically significant at 10% level, which suggests that there is no sample selection bias (see Table C.1).

[1] Beneficiary households are households that received input support mainly through NGOs. In many instances these were free gifts of seed and fertilizer targeted at vulnerable households.

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