Ex-post Impact Assessment of Fertilizer Microdosing as a Climate-Smart Technology in Sub-Saharan Africa

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Executive Summary

Microdosing refers to the application of small quantities of fertilizer with the seed at planting time or as top dressing three to four weeks after emergence. Microdosing provides sufficient nutrients especially on poor soils or degraded lands in amounts that are not too costly and are not damaging to the environment. Microdosing has been identified as a climate smart technology (The Montpellier Panel, 2013). Apart from being a climate smart technology, microdosing can be considered a pathway for the intensification of agricultural systems in Sub-Saharan Africa.

Microdosing technology was developed and promoted by ICRISAT and partner institutions over a decade ago to promote the use of fertilizers in the semi-arid tropics. The technology was developed after realising that crop yields in the semi-arid areas of Sub-Saharan Africa have been declining over time due to a decline in soil fertility resulting from mono-cropping, lack of fertilizer, unfavourable climatic conditions and low fertilizer use driven by the belief that inorganic fertilizers "burn crops". Despite the growing body of literature quantifying the impacts of microdosing on yields and farm income, there are few studies that have systematically quantified the impacts of microdosing on crop productivity and food security and building resilience under climate change.

Building on cross-sectional data from a recent survey on 415 smallholder farmers (193 microdosing adopters and 222 non-adopters) located in eight semi-arid districts of Zimbabwe, the results of this study demonstrate that microdosing increase crop production and productivity; reduce output and yield risk as well as improve food security. Such results have important policy implications for smallholder farmer's welfare in drought prone areas of Sub-Saharan Africa. In particular, these results demonstrate that microdosing is a welfare enhancing technology that potentially contributes to the first pillar of climate smart agriculture. Hence, the promotion of microdosing should be strengthened. Once farmers are convinced of the yield gains from using fertilizers, increased policy efforts should be placed not only on intensification of fertilizer use but on promoting fertilizer technologies such as microdosing that enhance nutrient use efficiency.

Based on the Just and Pope Production function corrected for sample selection, we found that fertilizer microdosing positively increase maize output, sorghum output and yield as well as cereal output in Zimbabwe. Furthermore microdosing reduced output and yield risks for maize and cereals. With regards, to the results from the endogenous switching probit model, we found that microdosing improves household food security. Among adopters, the adoption of microdosing increased the likelihood of being food secure by 47 percentage points compared to the counterfactual case. Based on the average treatment effects, microdosing increases the likelihood of being food secure by 17 percentage points. These findings demonstrate the importance of microdosing technology for enhancing the food security of smallholder farmers in semi-arid areas.

Data on the determinants of fertilizer use and microdosing technology suggest that farmer training on fertilizers; in particular microdosing increases the probability of using fertilizers and adoption of microdosing. Female headed households were less likely to microdose their crops, probably due to poor access to information by women. Receipt of fertilizer vouchers positively increases the probability of using fertilizers and adoption of microdosing. The data also suggest that fertilizer training is positively associated with the adoption of a portfolio of climate smart agricultural practices.

In addition to analysing a single climate smart agricultural practice: microdosing, we also did further analysis on the adoption and impacts of climate smart agricultural practices on maize. Farmers obtained higher maize yields when minimum tillage and manure application were combined with microdosing. This finding has important policy implications. Efforts to improve maize productivity should combine appropriate climate smart practices such as microdosing, minimum tillage and manure application that increase productivity while enhancing ecosystem resilience and sustainability.

1.0 Introduction

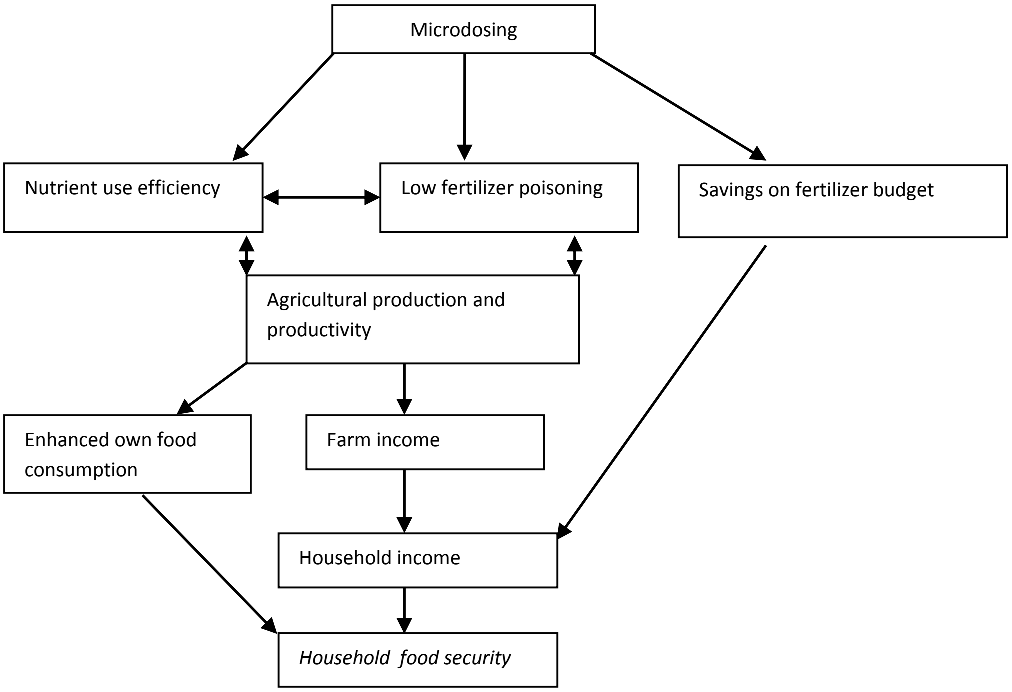
Climate Smart Agriculture (CSA) is defined by FAO (2010) as agricultural practices, approaches and systems that sustainably increase food production and ability of farmers to earn a living, while protecting and restoring the environment. CSA practices enable farmers to: sustainably increase agricultural productivity and incomes; adapt and build resilience to extreme weather events and a changing climate; and where appropriate, contribute to reducing greenhouse gas emissions and concentrations (FAO, 2010; Scherr et al., 2012). CSA consists of sustainable intensification practices such as conservation agriculture, microdosing, agroforestry, residue management and others (Scherr et al., 2012; The Montpellier Panel, 2013; Teklewold et al., 2013). Sustainable intensification practices aims to enhance the productivity and resilience of agricultural production systems while conserving the natural resource base (Teklewold et al., 2013; The Montpellier Panel, 2013). Therefore climate smart and sustainable intensification practices can be viewed as complements.

Microdosing is one sustainable intensification practice (The Montpellier Panel, 2013) that has been identified as a climate smart technology. Microdosing refers to the application of small quantities of fertilizer with the seed at planting time or as top dressing three to four weeks after emergence (Twomlow et al., 2010; Aune & Ousman, 2011; van der Velde, Marijn et al., 2013). Twomlow et al. (2010) highlights that microdosing provides sufficient nutrients especially on poor soils or degraded lands in amounts that are not too costly and are not damaging to the environment. Microdosing technology was developed and promoted by ICRISAT and partner institutions over a decade ago to promote the use of fertilizers in the semi-arid tropics (Chianu & Tsujii, 2005; Hayashi et al., 2008; Twomlow et al., 2010). The technology was developed after realising that crop yields in the semi-arid areas of Sub-Saharan Africa have been declining over time due to a decline in soil fertility resulting from mono-cropping, lack of fertilizer, unfavourable climatic conditions and low fertilizer use driven by the belief that inorganic fertilizers “burn crops” (Twomlow et al., 2010).

Microdosing contributes to CSA through various mechanisms. In Figure 1, we concentrate on the impact pathways of microdosing on the first pillar of CSA – of sustainably increasing agricultural productivity and incomes and food security. The first impact pathway is through higher nutrient use efficiency. Instead of spreading fertilizer over the entire field, microdosing results in higher nutrient use efficiency and ultimately improves productivity. Research results show that smallholder farmers’ investment in microdosing has demonstrated the potential of chemical fertilizers in some of the low-rainfall areas (Twomlow et al., 2010). Twomlow et al. (2010) assessed the impact of microdosing over three seasons in Zimbabwe. The study results showed that microdosing with nitrogen fertiliser (17 kg Nitrogen ha-1) could increase grain yields by 30 – 50% across a broad spectrum of soil, farmer management and seasonal climate conditions. Ncube et al. (2007) using on-farm trial results revealed that farmers could increase their yields by 50% by applying approximately 9 kg of nitrogen per hectare compared to no application in Zimbabwe. In West Africa, ICRISAT (2009) show that microdosing increased sorghum and millet yields by 44 to 120% and family incomes by 130%. Recently Winter- Nelson et al. (2013) found that microdosing increased maize and sorghum yields in Zimbabwe.

Second, microdosing potentially lowers the risk of fertilizer poisoning, and this is particularly relevant in the semi-arid areas where rainfall is erratic. Through higher nutrient use efficiency and reduced fertilizer poisoning, microdosing technology could enhance crop productivity. Increased crop production and productivity could enhance commercialization activities through higher marketable surplus thereby boosting household incomes. Improved household food security could then be realized from higher household incomes and enhanced own food production.

Figure 1 Impact pathways of microdosing to the first pillar of climate smart agriculture



Source: Authors computation

Third, microdosing saves on smallholder farmer’s fertilizer budget thereby ensuring more money remains in the hands of farmers. In addition, minimizing the use of fertilizer inputs contributes to the mitigation of climate change (Teklewold et al., 2013). Earlier studies have shown that microdosing is one technology that can be affordable to farmers and ensures that poor farmers get the highest returns from the fertilizer quantities that they are able to purchase (Twomlow et al., 2010). Chianu & Tsujii (2005) highlight that fertilizer costs is one of the reason for low fertilizer use in Africa. In addition, if fertilizer is used appropriately, it might reduce the variability of production (output risk) and improve welfare of farmers (Guttormsen & Roll, 2014). This is particularly important in semi-arid tropics that experience erratic and unpredictable weather patterns.

Apart from being a climate smart technology, microdosing can be considered a pathway for the intensification of agricultural systems in Sub-Saharan Africa. If farmers who don’t apply chemical fertilizers see the yield gains from microdosing, they may be nudged to start applying fertilizers to their crops. This is an important policy avenue considering that fertilizer use rates are low in Africa. Therefore exposure to microdosing through training, field demonstrations and trials is a critical component for farmers to adopt the technology. Based on the discussion above, microdosing can be viewed as a climate smart technology because it involves the altering of fertilizer rates and has the potential to boost crop production and productivity especially in drought-prone regions (Howden et al., 2007; Twomlow et al., 2010; Winter-Nelson et al., 2013).

Despite the growing body of literature quantifying the impacts of microdosing on yields (ICRISAT, 2009; Twomlow et al., 2010; Winter- Nelson et al., 2013) and farm income (ICRISAT, 2009), to the best of our knowledge there are few studies that have systematically quantified the impacts of microdosing on crop productivity and food security. Building on cross-sectional data from a recent survey in Zimbabwe, this article contributes to literature by analysing the impact of microdosing on crop productivity and food security. We use various econometric techniques to analyse the impacts of microdosing.

The article is organized as follows. In the next section we describe the evolution of microdosing in Sub-Saharan Africa. We then discuss the methodology - description of survey data and outcome measures used for empirical analysis, followed by the estimation strategy employed. Empirical results are presented and discussed. The last section concludes.

1.1 Background of fertilizer microdosing in Sub Saharan Africa

Throughout the 1980s and 1990s, ICRISAT primarily targeted the development and dissemination of early maturing varieties of sorghum and pearl millet as means to improve productivity and reduce the risks of drought in semi-arid agro-ecologies of Africa. Evidence suggests that adoption rates of the new varieties were favourable owing to their early maturity and large grain size. Unfortunately, limited gains were achieved in crop yields and productivity because of the low inherent fertility of most soils in the region and farmers' reluctance to risk investments in fertilizer.

In the late 1990s, ICRISAT started using crop simulation modeling to analyse how different soil fertility technologies behave under conditions of high rainfall variability. Simulation results for a 1951 to 1999 rainfall period in southern Zimbabwe suggested that farmers could increase their average yields by 50% by applying as little as 9 kg of nitrogen per hectare (Ncube et al., 2007; Twomlow et al., 2010; ICRISAT, 2009). These simulation results indicated that farmers were better off applying lower rates of nitrogen (microdosing) on multiple fields instead of concentrating a limited supply of fertilizer on one field. Micro-dosing involved the application of nitrogen fertilizer using a bottle cap per 3 plants at 4 to 6 weeks after crop emergence (Ncube et al., 2007; Twomlow et al., 2010). The microdosing application rate is a quarter to a third of the recommended rate in semi-arid areas of Zimbabwe. It is also recommended that at the time of fertilizer application, the field should be weed free and moist. The on-farm trial results revealed that farmers could increase their yields by 50% by applying approximately 9 kg of nitrogen per hectare compared to no application. (Ncube et al., 2007) argues that larger average gains could be obtained by combining the nitrogen fertilizer with a basal application of low grade manure.

Owing to its potential the promotion of microdosing was initiated in 2003/2004 agricultural season in Zimbabwe. Donors were already distributing seed and fertilizer inputs to drought affected farmers. Micro-dosing came as an essential intervention because farmers were not applying fertilizer at the recommended rates due to unavailability and unaffordability in the local markets. Financial and technical support for the promotion of microdosing of ammonium nitrate (AN) fertilizer to 170,000 farmers was obtained from the Department for International Development (DFID) and the European Commission Humanitarian Aid Office (ECHO) through the Protracted Relief Program (PRP). The promotion program included handing out pamphlets and posters on micro-dosing in local languages to recipients of relief fertilizer across the country. ICRISAT (2009) highlights the fertilizer microdosing has the potential to end widespread hunger in drought prone areas of Africa. The technology was expanded in

Zimbabwe, Mozambique and South Africa as well as in West African nations of Burkina Faso, Mali and Niger. In West Africa, ICRISAT (2009) show that microdosing increased sorghum and millet yields by 44 to 120% and increased family incomes by 50 to 130%.

2.0 Data collection and methodology

This study uses data collected from smallholder farmers located in eight semi-arid districts of Zimbabwe. A multi-stage stratification approach was used to draw the sample. In the first stage, three wards were selected in each district. Two wards captured households which were known to be exposed to microdosing technology based on the 5 year Conservation Agriculture panel study (Winter- Nelson et al., 2013). The third ward in each district was not exposed to microdosing (non-microdosing wards). The selection of the non-microdosing wards was done in consultation with local extension agents. During the survey, it was realized that some households in non-microdosing wards in Chivi, Masvingo and Zvishavane had actually received microdosing training. Therefore the classification into microdosing was done at plot level after the survey and based on information provided by respondents. In this study, a plot is considered to be microdosed if either basal or topdressing fertilizer was applied to the plot using the method of spot application. In addition, a household is considered to have adopted microdosing if it applied fertilizer on at least one plot using the spot application method. Farmers who spot apply usually use small quantities of fertilizer in contrast to banding and broadcasting methods and this is consistent with our definition of microdosing.

The data were collected through personal interviews using a pre-tested questionnaire during December 2012 and January 2013. The questionnaires were administered to the household head and/or the spouse. The data collected includes information on household demographics, crop and livestock production, training in microdosing, extension techniques, and fertilizer use and adoption, with particular attention paid to management practices and output on cereal plots two previous cropping seasons, household assets, and social networks. The survey covered 415 households of which 193 adopted microdosing and 222 are classified as non-adopters (Table 1).

Table 1: Microdosing survey sample differentiated by adoption status

District	Adopters	Non-adopters
Nkayi	21	29
Hwange	21	29
Zvishavane	33	19
Chivi	15	37
Masvingo	30	22
Chirumhanzu	40	12
Tsholotsho	16	39
Insiza	17	35
Total	193	222

Tables 2 show the details for the plots that were microdosed for each district differentiated by crop. The majority of farmers in our sample microdosed more maize plots compared to sorghum. This is expected as maize is the staple crop of the country and farmers usually apply new technologies to this crop.

Table 2: Microdosed plots for maize and sorghum

District	Maize		Sorghum	
	Plots microdosed	Plots not microdosed	Plots microdosed	Plots not microdosed
Nkayi	44	85	0	21
Hwange	33	43	23	71
Zvishavane	55	44	22	47
Chivi	20	61	6	57
Masvingo	57	49	2	15
Chirumhanzu	102	31	8	30
Tsholotsho	25	64	10	68
Insiza	32	80	7	37
Total	368	457	78	345

3.1 Estimation strategy

3.1.1 Bivariate probit model

The main focus of this study is to analyse impacts of microdosing. Households have to be using fertilizers first before they can adopt microdosing. Fertilizer use has spread rapidly in Zimbabwe since the 1980s. Nonetheless, not all households apply fertilizers to their crops. Second, not all households using fertilizers adopt microdosing, so that a first question of interest is as to what factors influence both the use of fertilizers and the adoption of microdosing innovation. Since microdosing adoption in this study is an outcome of fertilizer use, an econometric model has to be specified that takes into account a possible sample selection bias. Those farmers who are using fertilizers have a greater chance to successfully adopt microdosing than randomly selected farmers. As a result, the same unobservable factors that influence fertilizer use might also influence microdosing adoption. Hence, the two decisions are interrelated. The first stage includes all farmers and we estimate determinants of fertilizer adoption and second stage only considers fertilizer adopters and identifies determinants of microdosing adoption. In our setting, microdosing adoption is conditional on fertilizer adoption. To analyse this, we use a bivariate probit model with sample selection to control for potential selection bias (Greene, 2012; Kersting & Wollni, 2012). The bivariate probit model with sample selection is appropriate because it allows for two separate probit models with correlated error terms. If error terms are significantly correlated, this indicates the existence of a self-selection bias (Greene, 2012; Kersting & Wollni, 2012).

3.1.2 Just and Pope stochastic production function

In this subsection we are interested in analysing the impact of microdosing on maize, sorghum and cereal production and output risk in Zimbabwe. As discussed earlier, we argue that fertilizer microdosing is a climate smart agricultural practice that influences crop production. In order to determine the impact of microdosing on both the mean production and variability of crop output, we use a stochastic production function. In particular, we use the Just and Pope stochastic production function developed by Just & Pope (1979). The basic concept decomposes the production function into a deterministic one related to the output level and a second related to the variability of that output (Just & Pope, 1979; Isik & Devadoss, 2006). The approach allows for estimation of the impacts of an input variable, such as microdosing, on expected output and its variance (output risk). The Just and Pope production function is expressed as (Just & Pope, 1979; Isik & Devadoss, 2006; Cabas et al., 2010):

$$y = f(X,\beta) + \mu = f(X,\beta) + h(X,\alpha)^{0.5}\varepsilon \qquad (1)$$

where y is crop output or yield, X is a vector of explanatory variables, $f(.)$ is the mean function (or deterministic component of production) relating X to average output with β as the associated vector of estimated parameters, μ is a heteroscedastic disturbance term with a mean of zero; $h(X,\alpha)$ is the variance function (or stochastic component of output or yield) that relates X to the standard deviation of output with α as the corresponding vector of estimated parameters, and ε is a random error with zero mean and variance σ^2. From this formulation, inputs such as microdosing can independently influence mean output $\left(E(y) = f(X,\beta)\right)$ and output variance $(Var(y) = Var(\mu) = h(X,\alpha)\sigma^2)$.

The model expressed in equation (1) can be estimated using maximum likelihood estimation (MLE) or a three-step estimation procedure involving Feasible Generalized Least squares (FGLS) under heteroscedastic disturbances (Cabas et al., 2010; Isik & Devadoss, 2006; Chen et al., 2004). In this study, we use the FGLS. The three step FGLS takes the following steps. First, the model was estimated by Ordinary Least Squares (OLS) regression and the residuals $(\hat{\mu})$ are obtained.

$$\mathrm{y} = \mathrm{f}(\mathrm{X},\beta) + \mu \qquad (2)$$

In the second step, the logarithm of squared residuals was regressed on X.

$$\mathrm{In}(\hat{\mu}) = \mathrm{h}(\mathrm{X},\alpha) + \varepsilon \qquad (3)$$

Using this second stage estimation, variances are predicted. Using the square roots of these variances as weights, the output or yield model is re-estimated using the Weighted Least Squares (WLS) technique. In order to correct for endogeneity of microdosing adoption, we follow Koundouri & Nauges (2005) and apply the Heckman sample correction method to the Just and Pope Production function. In the first step, we estimated the Heckman two-step procedure and generate the Mills ratio. The Mills ratio is then incorporated into the Just and Pope Production function as an additional explanatory variable to control for selectivity bias. Failure to control for endogeneity of microdosing adoption would bias parameter estimates. Robust standard errors clustered at household level are used to account for multiple plots. In addition, in the variance function standard errors are bootstrapped. In the third stage of the Just and Pope Production function we correct mean regression for heteroscedasticity by using weights generated from the second stage.

The production function is specified with four inputs: namely plot size, labour, capital and fertilizer microdosing. Plot size is measured as the total area (in hectares) of the plot. Labour is proxied by the total number of household members aged 18-60 years who contribute to farm labour. The value of household assets is used to proxy capital. Fertilizer microdosing is measured as dummy variables indicating one if household microdosed the plot and zero otherwise. The model also includes management, demographic and socio-economic variables thought to influence production and productivity, including gender of household head, age of household head, farming experience, soil quality and rainfall among others.

While the majority of inputs in the econometric model are expected to increase crop output, some inputs may reduce the level of output risk, while others may increase risk. The Just and Pope production function is appropriate in situations when some inputs may decrease and others increase risks (Just & Pope, 1979). In the study area, agricultural production depends heavily on family labour. This is typical of most rural areas in Sub-Saharan Africa where mechanized agriculture is limited. Increasing the use of labour is expected to have a risk-reducing effect, as labour is crucial for crop management operations such as weeding and crop protection that enhance a health crop growth and reduce crop losses. Smallholder farmers in many developing countries do not receive the necessary training for applying fertilizer and as a result may poison their crops. Because of this fertilizer is regarded as a risk increasing input (Guttormsen & Roll, 2014; Just & Pope, 1979). In our case, fertilizer microdosing involves the application of small quantities of fertilizer appropriate to boost yields and reduce output risk in semi-arid areas. Therefore we expect that microdosing results in no crop poisoning and increases crop production and reduce output risk.

3.1.3 Endogenous switching probit model

Food security constitutes dimensions of food availability, stability, accessibility and utilization (FAO, 1996). Food security is multidimensional and this makes its measurement quite complex. There are several indicators that are used to measure food security. Barrett (2010) highlights a variety of objective measures of food security, e.g. dietary intake, expenditure, and health indicators. Haen et al. (2011), however argues that most of the approaches based on dietary intake and anthropometric indicators are expensive and data intensive. Maxwell et al. (2014) provides a review of the subjective indicators for example: dietary diversity and food frequency and self-assessment measures. The subjective measures are simple and easy to use but their main disadvantage is that they focus only on measuring food access and do not account for food intake and availability.

From our dataset, we use one subjective self-assessment measure of food security while acknowledging that food security is multidimensional which should be measured by multiple indicators. For the subjective food security measure, each household identified one category describing the food situation the household experienced as: 1 = We always have enough of every type of food that each person wants; 2 = We always have enough food for everyone, but not always the types of food that each person wants; 3 = We usually have enough food for everyone, but some people sometimes get less food than they want; 4 = We rarely have enough food for everyone to get enough; 5 = We never have enough food for everyone to get enough. In the analysis, we follow Winter- Nelson et al. (2013) and merge categories 1 and 2 into food-secure households, and categories 3, 4 and 5 into food-insecure households.

Our interest is to quantify the impacts of microdosing on household food security. Adopters and non-adopters are systemically different (see Table 3) and therefore it might be informative to estimate separate regressions for these two groups. A switching probit model is used for estimation because of the binary nature of our treatment and outcome variables (Lokshin & Sajaia, 2011). Consider a model with two binary outcome equations (whether food secure or not) and a criterion function MD_i that determines which regime the household faces. MD_i is a treatment variable denoting whether the household adopted microdosing or not. The treatment and the outcome can take one of the two potential values (Lokshin & Sajaia, 2011):

$$MD_i = 1 \quad if \;\; \gamma Z_i + \mu_i > 0 \qquad (4)$$

$$MD_i = 0 \quad if \;\; \gamma Z_i + \mu_i \leq 0$$

$$FS_{1i}^{*} = \beta_1 X_{1i} + \varepsilon_{1i} \quad FS_{1i} = I(FS_{1i}^{*} > 0) \qquad (5)$$

$$FS_{0i}^{*} = \beta_0 X_{0i} + \varepsilon_{0i} \quad FS_{0i} = I(FS_{0i}^{*} > 0) \qquad (6)$$

Observed FS_i is defined as

$$FS_i = FS_{1i} \quad if \quad MD_i = 1$$

$$FS_i = FS_{0i} \quad if \quad MD_i = 0$$

Where FS_{1i}^{*} and FS_{0i}^{*} are latent variables (household food security status) that defines the observed food security status FS_1 and FS_0 (whether household is food secure or not); Z_i and X_i are vectors of observables generating the selection equation and the food security equation; γ, β_1 and β_0 are the vector of parameters to be estimated. μ_i is the error term for the selection equation, ε_{1i} and ε_{0i} are the regime-specific error terms. μ_i, ε_{1i} and ε_{0i} are assumed to be jointly normally distributed, with a mean-zero vector.

One advantage of the endogenous switching probit model is that it offers the possibility of deriving probabilities in counterfactual cases for household's food security status on microdosing (Aakvik et al., 2005; Lokshin & Sajaia, 2011). In particular, it enables estimating the treatment effect on the treated (ATT), treatment effect on the untreated (ATU) and average treatment effect (ATE). For details on the computation of the treatment effects see Aakvik et al. (2005) and Lokshin & Sajaia (2011). The endogenous switching probit model is identified by nonlinearities of its functional form (Lokshin & Sajaia, 2011). The variables microdosing training and access to poster or pamphlet on microdosing were used as exclusion restriction to improve on identification. Khonje et al. (2015) and Shiferaw et al. (2014) also used access to information variables as exclusion restrictions.

3.1.4 Multinomial treatment effects regression

In the previous section, we have discussed econometric approaches to analyse the adoption and impacts of microdosing on crop output and yields. Farmers usually adopt a portfolio of different climate smart practices on their crops in an effort to maximize returns. Therefore focus on adoption and impacts of a single practice may be insufficient as this may fail to capture the complementarities and trade-offs between practices (Teklewold et al., 2013). We therefore improve our earlier analysis by analysing a combination of three climate smart agricultural practices (CSAP). These are also sustainable intensification practices. The first CSAP is minimum tillage. Minimum tillage reduces soil erosion and nutrient depletion while conserving soil moisture thus conserving the ecosystem (Teklewold et al., 2013; The Montpellier Panel, 2013). The second CSAP is manure application. Manure improves soil fertility and conserves soil moisture. The third CSAP is microdosing. Microdosing improves soil fertility and saves farmers costs of fertilizer (Twomlow et al., 2010). The minimum use of fertilizer also contributes to the mitigation of climate change.

In this section, we analyse the adoption of a combination of CSAPs and their impacts on maize yield. Specifically this section has two objectives. First, we analyse factors influencing the adoption of a combination of CSAPs (i.e., minimum tillage, manure and fertilizer microdosing) on maize crop in Zimbabwe. Second, we analyse the impacts of adopting various combinations of CSAPs on maize yield. The simultaneous adoption of minimum tillage, manure, and microdosing leads to eight possible combinations of CSAP that a farmer could choose. The actual choice is expected to be based on the farmer's expected utility derived from adoption given his/her constraints. We model farmers' choice of CSAP portfolios (i.e., alternative combinations of minimum tillage, manure, and microdosing) and outcome variable (maize yield) using a multinomial treatment effects regression (*mtreatreg*) (Deb & Trivedi, 2006).The *mtreatreg* according to Deb & Trivedi (2006) fits models with multinomial treatments and continuous, count and binary outcomes using maximum simulated likelihood. The *mtreatreg* model considers the effect of an endogenously chosen multinomial-valued treatment on an outcome variable, conditional on two sets of independent variables (Deb & Trivedi, 2006). The outcome variable can be continuous, binary or integer-valued while the treatment choice is assumed to follow a mixed multinomial logit distribution. The *mtreatreg* model is estimated using maximum simulated likelihood and the simulator uses Halton sequences (Deb & Trivedi, 2006). For a detailed discussion and model specification refer to Deb & Trivedi (2006).

4.0 Results and discussion

4.1 Descriptive analysis

The mean differences in outcome indicators and socio-economic characteristics between adopters and non-adopters are shown in Table 3. On average, households that adopted microdosing obtained higher yields for maize and sorghum and are also more food secure than households who did not adopt. These descriptive results suggest that these categories of households are systemically different. We now analyse differences in explanatory variables. Furthermore, more adopters received training on microdosing than non-adopters. This training was offered by NGOs in collaboration with ICRISAT and the public extension agency. Our results also show that adopters have better access to agricultural information through posters and pamphlets on microdosing compared to non-adopters. Access to agricultural information through microdosing training and posters is expected to enhance microdosing adoption only. Adopters have more access to social capital proxied by leadership in community compared to non-adopters. Access to social capital improves household access to information and resources. More adopters tend to apply fertilizer to their crops than non-adopters. Furthermore, more adopters received a fertilizer voucher compared to non-adopters. Adopters have on average higher asset values, more labour supply and bigger land sizes. Labour is an important input for enhancing agricultural production and productivity, which in turn could enhance food security. Land is an important investment in Zimbabwe. Households with bigger land holdings are likely to have higher output. Land is also used as collateral to secure loans to finance agricultural production.

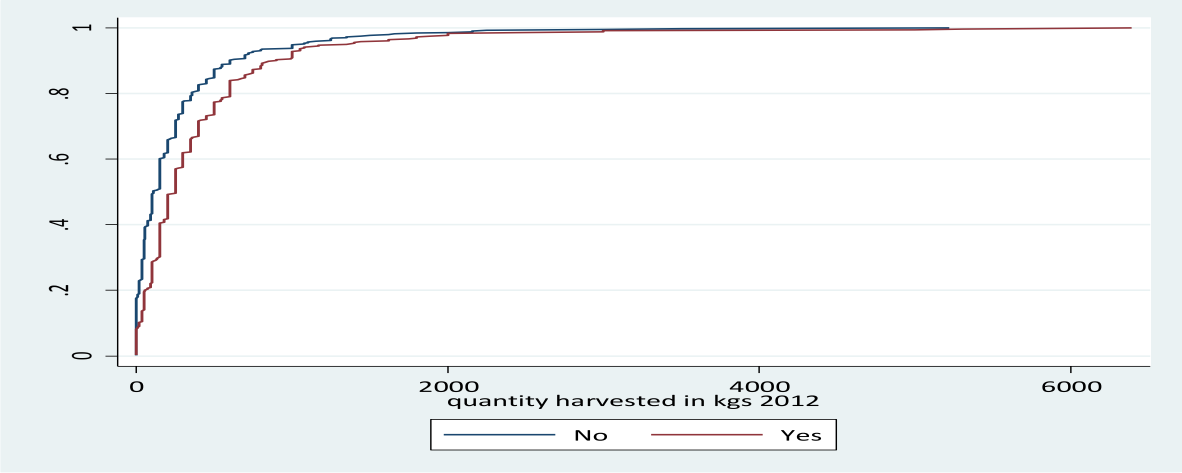
Table 3: Mean differences between adopters and non-adopters

Variable	Description	Adopters	Non-adopters	Differences
Outcome indicators				
Ln(Maize)	Maize yield (log)	6.734	6.302	-0.43***
Ln(Sorghum)	Sorghum yield (log)	6.408	5.960	-0.45***
Ln(Cereal)	Cereal output (log)	5.231	4.752	-0.48***
Food secure	Household food secure (1=yes)	0.668	0.446	-0.22***
Explanatory variables				
MD train	Household trained on microdosing	0.902	0.604	-0.30***
Poster/pamphlet	Got poster on microdosing (1=yes)	0.497	0.239	-0.26***
Leadership dummy	Household member leader in village (1=yes)	0.735	0.494	-0.24***
Fertilizer	Applied fertilizer to crops (1=yes)	0.720	0.159	-0.56***
Fertilizer voucher	Received fertilizer voucher (1=yes)	0.648	0.266	-0.38***
Labour	Adults 18-60 years contributing to farm work	3.466	3.090	-0.38**
Capital	Value of household assets ($000)	2.601	1.825	-0.78***
Plot hectares	Plot size in hectares	0.448	0.445	-0.00
Soil quality	Good soil quality	0.881	0.851	-0.03
Low rainfall	Located in low rainfall area	0.637	0.847	0.21***
Female head	Gender of head	0.228	0.317	0.09**
Age of head	Age	54.813	56.662	1.85
Farm expe	Farming experience(years)	27.461	28.414	0.95
Children 6-17	Number of children 6 to 17 years	2.259	2.342	0.08
Children under 6	Number of children under 6	0.943	1.131	0.19*
Dependency ratio	Dependency ratio	1.864	2.242	0.38**
Sick	Number sick	0.249	0.351	0.10
Total hectares	Land size	2.352	2.038	-0.31**
Hectares squared	Land size squared	7.418	5.953	-1.47
Number of observations		415	193	222

*, *** indicates the corresponding mean differences are significant at the 10%, 5% and 1% level (t-tests). Maize and sorghum yield calculated from 947 plots and cereal output from 1061 plots.

Figure 2 show the cumulative distribution functions (CDF) of maize output differentiated by microdosing status. The maize output distributions for microdosed plots and non-microdosed plots are statistically different. The CDF of maize output of microdosed plots clearly dominates that of non-microdosed plots. Here we assess whether the distribution with microdosing (first order) stochastically dominates the distribution without adoption, which means that the probability of average maize output falling below any threshold level is lower with the practice than without it (Mas-Colell et al., 1995). This suggests that the adoption of microdosing reduces risk as well as increase mean output.

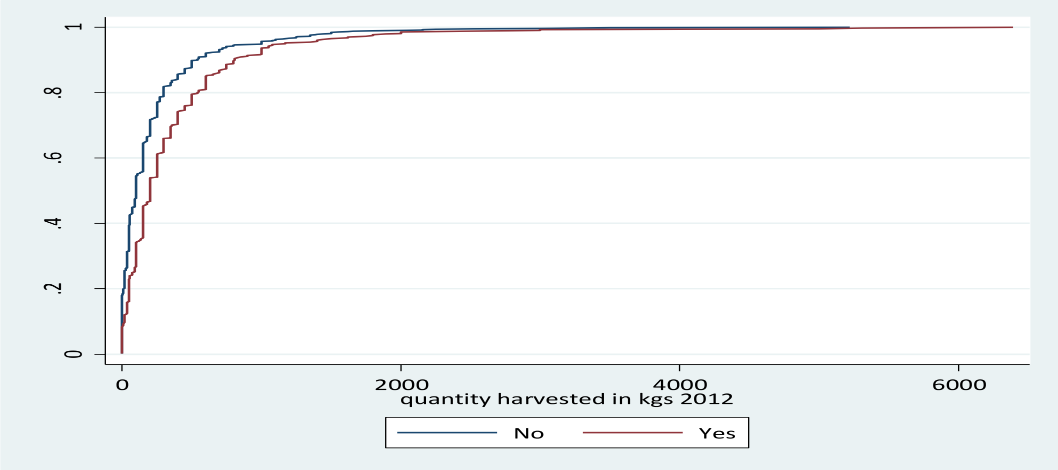
Figure 2: Cumulative distribution of maize output by microdosing status



Note: The Kolmogorov-Smirnov test statistic of 0.2141 indicates that the two distributions are statistically different (p= 0.000)

In figure 3, we present the CDF of cereal output differentiated by microdosing status. The cereal output distributions for plots that were microdosed are statistically different from non-microdosed plots. The CDF of cereal output for microdosed plots stochastically dominates that of non-microdosed plots.

Figure 3: Cumulative distribution of cereal output by microdosing adoption status



Note: The Kolmogorov-Smirnov test statistic of 0.2101 indicates that the two distributions are statistically different (p= 0.000)

Here, we provide the descriptive statistics of a combination of climate smart agricultural practices. The CSAPs considered in this study are minimum tillage, manure and fertilizer microdosing, providing eight possible combinations of CSAPs. Table 4 shows the proportions of maize area cultivated under different CSAP packages. Of the 825 maize plots, about 32% did not receive any of the CSAP ($T_0M_0F_0$), while the three practices were simultaneously adopted on 12% of the plots ($T_1M_1F_1$).

Table 4: A portfolio of CSAPs used on maize plots

Choice (j)	Binary triplet (package)	Minimum Tillage		Manure		Microdosing		Frequency (%)
		T_0	T_1	M_0	M_1	F_0	F_1	
1	$T_0M_0F_0$	√		√		√		31.52
2	$T_1M_0F_0$		√	√		√		1.58
3	$T_0M_1F_0$	√			√	√		14.18
4	$T_0M_0F_1$	√		√			√	15.64
5	$T_1M_1F_0$		√		√	√		8.12
6	$T_1M_0F_1$		√	√			√	2.55
7	$T_0M_1F_1$	√			√		√	14.79
8	$T_1M_1F_1$		√		√		√	11.654

Note: The binary triplet represents the possible CSAP combinations. Each element in the triplet is a binary variable for a CSAP: minimum tillage (T), manure (M) or microdosing (F). Subscript 1 = adoption and 0 = otherwise. In all econometric analysis that follows, we drop choices 2 and 6 because of few observations.

4.2 Econometric results

4.2.1 Fertilizer use and adoption of microdosing

Estimation results from the bivariate model explained above are shown in Table 5. The parameter *athrho* shown at the bottom panel of the table is significant and provides evidence for selection bias which is controlled for by the bivariate probit model with sample selection. This shows that the bivariate model is appropriate. The coefficients show the direction of impact of the explanatory variables on fertilizer use and microdosing adoption. Several variables turn out to be significant in explaining fertilizer use and microdosing adoption. Holding all others constant, the results show that microdosing training increases the probability of using fertilizer and adoption of microdosing. This has important policy implications for both extension and the intensification of agricultural systems. Fertilizer training should be a core component of the extension messages to stimulate farmers to use fertilizers. Female headed households are less likely to practice microdosing on their crops. This can be a reflection of poor access to information by farmers. Receipt of fertilizer vouchers positively increases the probability of using fertilizers and microdosing adoption. In line with Winter- Nelson et al. (2013) environmental factors have a strong influence on both the probability of fertilizer use and microdosing. Households residing in NR III which receive higher rainfall are more likely to use fertilizers and adopt microdosing than those in NR IV. In addition households residing in NR V are less likely to use fertilizers, owing to low rainfall patterns.

Table 5: Bivariate probit model estimates – applied fertilizer and practised microdosing

	Applied fertilizer		Microdosed	
	Coef	Std. err.	Coef	Std. err.
Soil quality	0.013	0.214	-0.013	0.212
Plot hectares	0.271***	0.088	0.002	0.085
MD training	0.733***	0.251	0.671***	0.256
Agritex	-0.106	0.177	0.032	0.181
Poster/pamphlet	-0.038	0.163	0.317*	0.163
Female head	-0.147	0.169	-0.333**	0.168
Age of head	-0.002	0.009	-0.015*	0.009
Farming experience	-0.014	0.009	0.001	0.009
Fertilizer voucher	0.999***	0.156	0.912***	0.155
NR3	0.745***	0.186	0.913***	0.190
NR5	-0.556**	0.254	-0.468*	0.246
Children under 6	-0.074	0.076	-0.050	0.073
Children 6 -16	0.076	0.047	-0.026	0.046
Sick	-0.002	0.093	-0.051	0.110
Adults	0.057	0.056	0.026	0.058
Total hectares	0.128	0.167	0.271*	0.161
Hectares squared	-0.016	0.023	-0.032	0.022
Capital	0.088	0.062	0.057	0.063
Constant	-1.514***	0.567	-1.159**	0.569
N	402			
Log likelihood	-384.297			
Athrho	0.821***	0.115		

*, **, *** indicates the corresponding coefficients are significant at the 10%, 5%, and 1% levels, respectively.

4.2.2 Impact of microdosing on maize production and productivity

The econometric results in Table 6 show the Just & Pope Production estimates corrected for sample selection. The results show that adoption of microdosing has a positive and significant impact on maize production. The adoption of microdosing increases maize production by 1.40%[1] and this agrees with our hypothesis that microdosing has a positive impact on production.

As discussed earlier the production or yield risk is captured by the variance function in the Just and Pope Production framework. In order to disentangle the effect of the technology from the pure fertilizer effect, we included the quantity of fertilizer applied as an additional variable. We interpret the elasticities of the variance function by looking directly at the parameter estimates from the variance function in Table 6 (Guttormsen & Roll, 2014). Microdosing is negative and significant, in both maize output and yield risk functions. Microdosing reduce maize output and yield variability by 0.47% and 0.43% respectively.

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[1] Obtained by specifying display exp(0.333) in STATA

Table 6: Impact of microdosing on maize production and productivity

	Maize production		Maize yield	
	Output	Output risk	Yield	Yield risk
Microdosing	0.333*	-0.759***	0.159	-0.844***
	(0.180)	(0.241)	(0.139)	(0.294)
Plot size	0.732***	0.475*	-0.923***	-0.462
	(0.166)	(0.257)	(0.147)	(0.357)
Ln(labour)	0.388***	-0.389*	0.151	0.091
	(0.139)	(0.206)	(0.135)	(0.246)
Ln(capital)	0.048	0.071	0.098**	-0.052
	(0.051)	(0.086)	(0.047)	(0.113)
Fertilizer	0.006***	-0.002	0.006***	0.003
	(0.002)	(0.003)	(0.002)	(0.004)
Soil quality	0.237	0.248	-0.195	0.174
	(0.207)	(0.473)	(0.166)	(0.396)
Low rainfall	-0.277**	-0.225	-0.162	-0.128
	(0.133)	(0.219)	(0.117)	(0.266)
Female head	-0.188	-0.212	-0.103	0.309
	(0.144)	(0.281)	(0.137)	(0.250)
Age of head	0.015***	-0.008	0.018***	-0.012
	(0.003)	(0.009)	(0.004)	(0.012)
Farming experience	0.011**	0.010	0.002	0.012
	(0.006)	(0.011)	(0.006)	(0.016)
Dependency ratio	0.039	-0.011	0.018	0.022
	(0.041)	(0.066)	(0.038)	(0.063)
Sick	-0.134	0.297	0.139	0.360*
	(0.189)	(0.211)	(0.113)	(0.201)
Total hectares	-0.194*	0.270	-0.388***	0.133
	(0.116)	(0.215)	(0.140)	(0.261)
Hectares squared	0.019	-0.029	0.045**	-0.001
	(0.014)	(0.028)	(0.020)	(0.032)
Mills ratio	-0.102	0.708	-0.288	-0.043
	(0.316)	(0.445)	(0.268)	(0.515)
Constant	3.306***	-1.488	6.526***	-1.123
	(0.460)	(0.976)	(0.429)	(0.958)
Number of plots	518	518	488	488
Log likelihood	-656.621	-1138.887	-582.389	-1089.362

*, **, *** indicates the corresponding coefficients are significant at the 10%, 5%, and 1% levels, respectively. Output and yield are log transformed. Standard errors are shown in parenthesis. Standard errors in the risk function are bootstrapped.

Such a result corroborates with our expectation, that microdosing reduces output and yield risk. This is partly because microdosing reduces the possibility of fertilizer poisoning when low and erratic rainfall is experienced. For maize, our results show that microdosing increases maize output, stabilize output and yields in semi-arid areas of Zimbabwe. These results that microdosing increases maize production and stabilize yields suggests that microdosing contributes to the first pillar of climate smart agriculture.

Labour positively increases maize output. Labour is important for crop management operations such as planting, weeding, fertilization and harvesting that are critical and enhances a healthy crop growth. Though labour is negative in the variance function it is not significant. This contradicts with Guttormsen & Roll (2014) who found that labour has a risk-reducing effect on crop production. Capital is important for crop production. Our results show that capital is positive and highly significant in the yield function. Fertilizer has a positive and significant effect on both maize output and yield.

4.2.3 Impact of microdosing on sorghum production and productivity

The econometric results in table 7 show that microdosing have a significant impact on sorghum output and yield. The result that microdosing positively influences sorghum production and productivity is a confirmation that microdosing contributes to the first pillar of climate smart agriculture (of boosting productivity). Sorghum is one of the predominant crops in the semi-arid areas of Zimbabwe and our results have significant policy implications. The policy implication is that microdosing should be promoted among sorghum growers to boost production and productivity. The other variables: labour, capital, fertilizer and farming experience are all positive and significant in explaining sorghum output and productivity. Low rainfall and older farm households tend to be associated with lower sorghum output and yields. In terms of risk, results show that microdosing has no impact on sorghum output and yield variability.

Table 7: Impact of microdosing on sorghum production and productivity

	Sorghum production		Sorghum yield	
	Output	Output risk	Yield	Yield risk
Microdosing	0.387*	0.649	0.616***	-0.957
	(0.223)	(0.810)	(0.213)	(0.729)
Plot size	0.514**	0.272	0.554***	-0.349
	(0.257)	(0.514)	(0.153)	(0.863)
Ln(labour)	0.483**	0.071	0.246***	-0.057
	(0.215)	(0.476)	(0.072)	(0.333)
Ln(capital)	0.216**	0.877**	0.010***	-0.224
	(0.094)	(0.347)	(0.003)	(0.876)
Fertilizer	0.015***	0.014	-0.771***	0.003
	(0.004)	(0.011)	(0.204)	(0.012)
Soil quality	0.273**	0.515	0.373	-1.004
	(0.130)	(0.703)	(0.236)	(0.776)
Low rainfall	-0.394**	0.464	-0.451**	1.152
	(0.172)	(0.710)	(0.198)	(0.724)
Female head	-0.048	0.053	0.138	0.369
	(0.236)	(0.772)	(0.224)	(0.767)
Age of head	-0.049***	-0.028	-0.058***	0.005
	(0.014)	(0.051)	(0.012)	(0.052)
Farming experience	0.042***	-0.027	0.053***	0.034
	(0.009)	(0.040)	(0.010)	(0.047)
Dependency ratio	-0.027	0.225	-0.027	-0.227
	(0.052)	(0.212)	(0.053)	(0.277)
Sick	-1.075**	0.530	-0.030	-1.194
	(0.466)	(0.645)	(0.109)	(0.850)
Total hectares	0.243	-0.103	0.444***	-0.211
	(0.203)	(0.583)	(0.140)	(0.532)
Hectares squared	-0.030	-0.034	-0.049***	0.013
	(0.018)	(0.076)	(0.011)	(0.055)
Mills ratio	0.819***	-0.493	0.227	-0.342
	(0.227)	(0.914)	(0.311)	(0.892)
Constant	3.406***	-1.090	5.564***	-0.560
	(0.696)	(2.210)	(0.716)	(2.536)
Number of plots	110	110	95	95
Log likelihood	-91.264	-245.286	-63.675	-214.200

*, **, *** indicates the corresponding coefficients are significant at the 10%, 5%, and 1% levels, respectively. Output and yield are log transformed. Standard errors are shown in parenthesis. Standard errors in the risk function are bootstrapped.

4.2.4 Impact of microdosing on cereal production and productivity

In Table 8, we present econometric results of the impact of microdosing on cereal output and productivity. The cereals used in the analysis include maize, sorghum and pearl millet. The regression coefficient for microdosing is positive and significant at the 10% level in the mean output function and insignificant in the yield function. Microdosing increases cereal output by 1.31%. Microdosing has a negative and significant effect in both the output and yield variance functions, suggesting the technology has a risk-reducing effect. These results show the importance of microdosing on stabilising cereal output and yields.

The other variables that increase cereal output are capital, plot size, capital, fertilizer, soil quality and farming experience. Residing in a low rainfall area reduces cereal output. Capital and age of household head positively influences cereal productivity. Surprisingly, and unexpectedly fertilizer turns out to be negative and significant in influencing cereal yields.

Table 8: Impact of microdosing on cereal production and productivity

	Cereal production		Cereal yield	
	Output	Output risk	Yield	Yield risk
Microdosing	0.268*	-0.397*	0.172	-0.410**
	(0.143)	(0.226)	(0.110)	(0.206)
Plot size	0.391***	-0.099	0.153	0.199
	(0.138)	(0.178)	(0.120)	(0.202)
Ln(labour)	0.043	0.108	0.085*	-0.049
	(0.044)	(0.099)	(0.045)	(0.087)
Ln(capital)	0.008***	-0.004	0.007***	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Fertilizer	0.773***	0.593**	-0.787***	-0.049
	(0.152)	(0.231)	(0.157)	(0.272)
Soil quality	0.474***	-0.052	-0.048	-0.204
	(0.166)	(0.253)	(0.159)	(0.258)
Low rainfall	-0.359***	0.061	-0.218**	0.145
	(0.120)	(0.210)	(0.110)	(0.194)
Female head	-0.213	-0.471*	-0.070	0.373**
	(0.142)	(0.260)	(0.143)	(0.188)
Age of head	0.009	-0.006	0.013**	-0.005
	(0.006)	(0.010)	(0.006)	(0.010)
Farming experience	0.014**	0.016	0.004	0.011
	(0.006)	(0.013)	(0.007)	(0.012)
Dependency ratio	0.040	0.033	0.000	0.060
	(0.037)	(0.061)	(0.038)	(0.053)
Sick	-0.166	0.185	0.154	0.240
	(0.187)	(0.311)	(0.108)	(0.161)
Total hectares	-0.173*	0.161	-0.316***	-0.022
	(0.100)	(0.178)	(0.118)	(0.164)
Hectares squared	0.014	-0.023	0.032**	0.008
	(0.011)	(0.020)	(0.016)	(0.021)
Mills ratio	0.120	0.162	-0.368*	-0.075
	(0.228)	(0.377)	(0.192)	(0.326)
Constant	3.060***	-1.546**	6.595***	-1.342*
	(0.448)	(0.702)	(0.405)	(0.726)
Number of plots	628	628	583	583
Log likelihood	-837.690	-1379.708	-717.296	-1211.453

*, **, *** indicates the corresponding coefficients are significant at the 10%, 5%, and 1% levels, respectively. Output and yield are log transformed. Standard errors are shown in parenthesis. Standard errors in the risk function are bootstrapped.

4.2.5 Impact of microdosing on food security

Table 9 presents the econometric results of the impact of microdosing on household food security. Endogenous switching probit model is used for estimation. Capital positively influenced the likelihood of households being food secure for non-adopters only. Capital proxied by value of household assets is important for boosting agricultural production and productivity. Higher agricultural productivity and commercialization may in turn improve household food consumption and liquidity which is crucial for food security. Land size has a positive and significant effect on increasing the likelihood of being food secure for microdosing adopters only. Adopting households with large land holdings are more likely to be food secure. Low rainfall has a negative and significant effect for adopters only. For non-adopters, having more dependents decreases the likelihood of being food secure. These results show that dependents increase the risk of food insecurity among non-adopters.

Table 9: Impact of microdosing on food security

	Selection		Adopters		Non-adopters	
	Coef	Std. err.	Coef	Std. err.	Coef	Std. err.
Ln(capital)	-0.052	0.074	0.094	0.116	0.257**	0.103
Age of head	-0.015**	0.007	-0.002	0.011	-0.006	0.010
Female head	-0.402**	0.196	-0.474	0.315	-0.110	0.251
Low rainfall	-1.313***	0.213	-1.548***	0.340	0.067	0.329
Dependency ratio	-0.028	0.052	-0.119	0.087	-0.118*	0.066
Ln(labour)	-0.181	0.201	-0.650**	0.306	-0.164	0.229
Ln(Farm size)	0.190	0.158	0.628**	0.245	0.092	0.195
Leadership dummy	0.333*	0.188	-0.042	0.290	0.244	0.241
MD training	0.390	0.263	1.385***	0.444	0.170	0.262
Fertilizer voucher	1.080***	0.200				
Poster/pamphlet	0.324*	0.180				
Sick			-0.007	0.248	0.122	0.150
Constant	1.136*	0.602	0.095	0.883	-1.955**	0.770
athrho1, athrho0			0.337	0.514	-1.159	0.726
LR test of indep. eqns.	*4.97***					
N	281					
Log likelihood	-289.077					

*, **, *** indicates the corresponding coefficients are significant at the 10%, 5%, and 1% levels, respectively.

The effect of microdosing on food security is presented in Table 10 which is estimated following Lokshin & Sajaia (2011) approach of computing treatment effects. The average treatment effect on the treated (ATT) was 0.472. This implied that among adopters, the adoption of microdosing led to about 47 percentage points more likelihood of being food secure compared to the counterfactual case (not adopting microdosing). Based on the average treatment effects (ATE) regression results show that adoption of microdosing increases the likelihood of being food secure by 17 percentage points. These findings demonstrate that microdosing is important for food security among smallholder farmers in semi-arid areas. This is consistent with the view that adoption of new agricultural innovations can improve household welfare in developing countries (Shiferaw et al., 2014; Khonje et al., 2015).

Table 10: Mean treatment effect from microdosing

Treatment effects	Estimate	Std. err.
Average treatment effect on the treated (ATT)	0.472	0.018
Average treatment effect (ATE)	0.167	0.016

4.2.6 Factors explaining the adoption of a portfolio of CSAP

The results from the multinomial logit model are presented in Table 11. The base category is non-adoption ($T_0M_0F_0$), where econometric results are compared. The Wald test that all regression coefficients are jointly equal to zero is rejected$[\mathrm{X}^2 = 870.34; p = 0.000]$. This implies that the model fits the data well. The results in column 2 to 6 show the estimated coefficients for different packages.

The adoption of $T_0M_0F_1$, $T_1M_1F_0$, $T_0M_1F_1$ and $T_1M_1F_1$ is positively influenced by microdosing training and residing in Natural Region 3. The implication is that farmer training on fertilizers is crucial for the adoption of a package of CSAP. Farmer training could be achieved through lectures, demonstration plots and print material. Asset value has a positive influence on the adoption of manure and microdosing package only (T0M1F1). Safe plot location highly influences the adoption of $T_0M_1F_0$, T1M1F0, $T_0M_1F_1$ and $T_1M_1F_1$ with the exception of microdosing ($T_0M_0F_1$). Safe maize plots offer protection from stray animals and include those nearer to homesteads and/or fenced. This is expected as farmers put investments on protected fields. Safe plot location increase the adoption of CSAPs therefore the policy implications is to encourage smallholder farmers to fence and protect their plots.

4.2.7 Impact of a combination of CSAP on maize productivity

The second stage estimates on the impacts of a combination of CSAP on maize yields are reported in Table 11, column 7. Our interest is on the impacts of different combinations of CSAPs shown in the bottom panel of the Table. We found that for farmers who adopted packages ($T_0M_1F_0$ and $T_0M_0F_1$) had average maize yield that were not significantly higher than it would have been if the adopters had adopted $T_0M_0F_0$. The result that adopting microdosing in isolation ($T_0M_0F_1$) has no effect on maize yields is consistent with our earlier results in Table 6. The adoption of $T_1M_1F_0$, $T_0M_1F_1$ and $T_1M_1F_1$ significantly increased maize yields. In almost all cases, the adoption of a combination of CSAPs provides higher maize yield compared to adopting each CSAP in isolation. Farmers obtained higher maize yields when minimum tillage and manure application were combined with microdosing. The largest yield effect is from adoption of the package $T_1M_1F_1$.

Table 11: Adoption and impact of a portfolio of CSAPs on maize

	$T_0M_1F_0$	$T_0M_0F_1$	$T_1M_1F_0$	$T_0M_1F_1$	$T_1M_1F_1$	Yield
Female head	-0.156	-0.240	-0.110	-0.127	-0.592	-0.074
	(0.410)	(0.421)	(0.466)	(0.411)	(0.436)	(0.101)
Age of head	-0.005	-0.016	-0.045	-0.021	0.023	0.005
	(0.017)	(0.021)	(0.028)	(0.019)	(0.021)	(0.004)
Farm experience	0.016	-0.010	0.051*	-0.012	-0.027	0.001
	(0.018)	(0.020)	(0.028)	(0.021)	(0.021)	(0.005)
MDTward	0.610	1.704***	1.778***	1.299**	1.597***	0.342***
	(0.432)	(0.559)	(0.569)	(0.511)	(0.523)	(0.125)
NR3	0.319	1.958***	1.414***	2.265***	2.680***	0.144
	(0.448)	(0.466)	(0.483)	(0.439)	(0.499)	(0.125)
NR5	-0.072	-0.997	0.454	-0.311	1.323**	-0.402
	(0.539)	(0.798)	(0.630)	(0.722)	(0.671)	(0.268)
Sick	0.176	0.138	-0.132	-0.217	0.340	0.022
	(0.328)	(0.350)	(0.387)	(0.316)	(0.396)	(0.113)
Negative shock	0.063	-0.337**	-0.168	0.115	0.021	0.062**
	(0.084)	(0.143)	(0.165)	(0.091)	(0.135)	(0.030)
Adults	0.196	0.141	-0.046	0.063	0.205	-0.011
	(0.134)	(0.150)	(0.168)	(0.130)	(0.163)	(0.044)
Asset value	0.075	0.098	-0.128	0.267***	0.073	0.084***
	(0.074)	(0.074)	(0.140)	(0.057)	(0.083)	(0.021)
Plot size	1.077***	-0.724*	-1.593**	0.396	-2.398**	-0.555***
	(0.416)	(0.439)	(0.757)	(0.423)	(1.044)	(0.198)
Plot location	0.845**	-0.423	2.225***	0.938***	1.690***	0.064
	(0.331)	(0.349)	(0.527)	(0.340)	(0.387)	(0.079)
Total hectares	-0.696*	0.817*	-0.558	0.165	0.606	-0.188
	(0.372)	(0.434)	(0.418)	(0.419)	(0.408)	(0.120)
Hectares squared	0.053	-0.090	0.081*	-0.021	-0.045	0.019
	(0.051)	(0.060)	(0.049)	(0.057)	(0.050)	(0.014)
$T_0M_1F_0$						0.036
						(0.126)
$T_0M_0F_1$						-0.045
						(0.176)
$T_1M_1F_0$						0.542***
						(0.169)
$T_0M_1F_1$						0.355**
						(0.150)
$T_1M_1F_1$						1.006***
						(0.146)
Constant	-2.311**	-2.486**	-2.126	-2.977***	-5.931***	3.748**
	(0.919)	(1.155)	(1.310)	(1.065)	(1.156)	(1.528)
Lambda	0.487**	0.347**	-0.234**	-0.074	-0.479***	
	(0.245)	(0.175)	(0.106)	(0.102)	(0.131)	
Lnalpha	2.276					
	(1.480)					
N	619					
ll	-5752.829					

Note: ***, **, * significant at 1%, 5%, and 10% level, respectively. Numbers in parenthesis are standard errors clustered at household level.

5. Conclusion

The goal of CSA according to FAO (2010) is to simultaneously achieve increased agricultural productivity and incomes (food security), improved resilience to climate change (adaptation) and reduction of greenhouse gas emissions (mitigation). In this article, we focus on the impact of microdosing on agricultural productivity and food security – the first pillar of climate smart agriculture. We used cross section data from a recent survey conducted on 415 farm households in Zimbabwe.

Before presenting results of the impact of microdosing, we first present the determinants of fertilizer use and microdosing technology. Results from the bivariate probit model show that farmer training on fertilizers; in particular microdosing increases the probability of using fertilizers and adoption of microdosing. Female headed households were less likely to microdose their crops, probably due to poor access to information by women. Receipt of fertilizer vouchers positively increases the probability of using fertilizers and adoption of microdosing. Results from the multinomial treatment effects model show that fertilizer training is positively associated with the adoption of a portfolio of CSAPs. This further reinforces the importance of farmer training. These results have important policy implications for both extension in Zimbabwe, and fits perfectly to the emerging discussion and policy thrust on the intensification of agricultural systems in Africa. Fertilizer training should be a core component of the extension messages to stimulate farmers to use fertilizers. Government and private sector should invest in the promotion of fertilizer microdosing through increased awareness and technical training. Training farmers is crucial for increasing uptake of fertilizer microdosing in Zimbabwe. The training could be in form of lectures, demonstration trials as well as distribution of print materials (e.g. posters etc) to farmers.

The results of this study suggest that fertilizer microdosing positively increase maize output, sorghum output and yield as well as cereal output in Zimbabwe. Microdosing reduces output and yield risks for maize and cereals. Furthermore, microdosing improves household food security. Among adopters, the adoption of microdosing increases the likelihood of being food secure by 47 percentage points compared to the counterfactual case. Moreover, microdosing increases the likelihood of being food secure by 17 percentage points. These findings demonstrate the importance of microdosing technology for enhancing the food security of smallholder farmers in semi-arid areas.

In addition to analysing a single climate smart agricultural practice: microdosing, we also did further analysis on the adoption and impacts of a portfolio of CSAPs on maize. The results modelling the portfolio of CSAPs have important policy implications. First, they highlight the importance of training on fertilizer and protecting crop fields on the adoption of a portfolio of CSAPs. Second, adoption of CSAPs increases maize yield, and the highest payoff is achieved when CSAPs are adopted in combination rather than in isolation. Farmers obtained higher maize yields when minimum tillage and manure application were combined with microdosing. The finding that the adoption of the combined CSAPs has a positive effect on maize productivity has important policy implications. Efforts to improve maize productivity should combine microdosing with appropriate climate smart practices such as minimum tillage and manure application that increase productivity while enhancing ecosystem resilience and sustainability.

References

Aakvik, A., Heckman, J. J., & Vytlacil, E. J. (2005). Estimating treatment effects for discrete outcomes when responses to treatment vary: an application to Norwegian vocational rehabilitation programs. *Journal of Econometrics*, *125*, 15–51.

Aune, J. B., & Ousman, A. (2011). Effect of seed priming and micro-dosing of fertilizer on sorghum and pearl millet in Western Sudan. *Experimental Agriculture*, *47*, 419–430.

Barrett, C. B. (2010). Measuring food insecurity. *Science (New York, N.Y.)*, *327*, 825–828.

Cabas, J., Weersink, A., & Olale, E. (2010). Crop yield response to economic, site and climatic variables. *Climatic Change*, *101*, 599–616.

Chen, C.-C., McCarl, B. A., & Schimmelpfennig, D. E. (2004). Yield Variability as Influenced by Climate: A Statistical Investigation. *Climatic Change*, *66*, 239–261.

Chianu, J. N., & Tsujii, H. (2005). Determinants of farmers? decision to adopt or not adopt inorganic fertilizer in the savannas of northern Nigeria. *Nutrient Cycling in Agroecosystems*, *70*, 293–301.

Deb, P., & Trivedi, P. K. (2006). Maximum simulated likelihood estimation of a negative binomial regression model with multinomial endogenous treatment. *The Stata Journal*, *6*, 246–255.

FAO (1996). *The Rome Declaration on World Food Security. The World Food Summit*. FAO, Rome.

FAO (2010). Sourcebook on Climate-Smart Agriculture, Forestry and Fisheries. http://www.fao.org/climate-smart-agriculture/72611/en/. Accessed 13.11.2014.

Greene, W. H. (2012). *Econometric analysis.* (7th ed). Boston: Prentice Hall.

Guttormsen, A. G., & Roll, K. H. (2014). Production Risk in a Subsistence Agriculture. *The Journal of Agricultural Education and Extension*, *20*, 133–145.

Haen, H. de, Klasen, S., & Qaim, M. (2011). What do we really know? Metrics for food insecurity and undernutrition. *Food Policy*, *36*, 760–769.

Hayashi, K., Abdoulaye, T., Gerard, B., & Bationo, A. (2008). Evaluation of application timing in fertilizer micro-dosing technology on millet production in Niger, West Africa. *Nutrient Cycling in Agroecosystems*, *80*, 257–265.

Howden, S. M., Soussana, J.-F., Tubiello, F. N., Chhetri, N., Dunlop, M., & Meinke, H. (2007). Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences of the United States of America*, *104*, 19691–19696.

ICRISAT (2009). *Fertilizer Microdosing, Boosting production in unproductive lands*. ICRISAT-Patancheru.

Isik, M., & Devadoss, S. (2006). An analysis of the impact of climate change on crop yields and yield variability. *Applied Economics*, *38*, 835–844.

Just, R. E., & Pope, R. D. (1979). Production Function Estimation and Related Risk Considerations. *American Journal of Agricultural Economics*, *61*, 276.

Kersting, S., & Wollni, M. (2012). New institutional arrangements and standard adoption: Evidence from small-scale fruit and vegetable farmers in Thailand. *Food Policy*, *37*, 452–462.

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development*, *66*, 695–706.

Koundouri, P., & Nauges, C. (2005). On Production Function Estimation with Selectivity and Risk Considerations. *Journal ofAgricultura1 and Resource Economics*, *30*, 597–608.

Lokshin, M., & Sajaia, Z. (2011). Impact of interventions on discrete outcomes: Maximum likelihood estimation of the binary choice models with binary endogenous regressors. *The Stata Journal*, *11*, 368–385.

Mas-Colell, A., Whinston, M. D., & Green, J. R. (1995). *Microeconomic theory*. New York: Oxford University Press.

Maxwell, D., Vaitla, B., & Coates, J. (2014). How do indicators of household food insecurity measure up? An empirical comparison from Ethiopia. *Food Policy*, *47*, 107–116.

Ncube, B., Dimes, J. P., Twomlow, S. J., Mupangwa, W., & Giller, K. E. (2007). Raising the productivity of smallholder farms under semi-arid conditions by use of small doses of manure and nitrogen: a case of participatory research. *Nutrient Cycling in Agroecosystems*, *77*, 53–67.

Scherr, S. J., Shames, S., & Friedman, R. (2012). From climate-smart agriculture to climate-smart landscapes. *Agriculture & Food Security*, *1*, 12.

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, *44*, 272–284.

Teklewold, H., Kassie, M., Shiferaw, B., & Köhlin, G. (2013). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics*, *93*, 85–93.

The Montpellier Panel (2013). *Sustainable Intensification: A New Paradigm for African Agriculture*. Imperial College London, London.

Twomlow, S., Rohrbach, D., Dimes, J., Rusike, J., Mupangwa, W., Ncube, B., Hove, L., Moyo, M., Mashingaidze, N., & Mahposa, P. (2010). Micro-dosing as a pathway to Africa's Green Revolution: evidence from broad-scale on-farm trials. *Nutrient Cycling in Agroecosystems*, *88*, 3–15.

van der Velde, Marijn, See, L., You, L., Balkovič, J., Fritz, S., Khabarov, N., Obersteiner, M., & Wood, S. (2013). Affordable nutrient solutions for improved food security as evidenced by crop trials. *PloS one*, *8*, e60075.

Winter- Nelson, A., Stack, J., Mvumi, B., & Pedzisa, T. (2013). *Impact of Fertilizer Micro dosing Research and Development in Semi-arid Zimbabwe. Report produced for the International Crops Research Institute for the Semi-Arid Tropics*. ICRISAT.