# A Matching Approach to Analyze the Impact of New Agricultural Technologies: Productivity and Technical Efficiency in Niger

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**Abstract**

In this paper we assess the performance of farmers adopting an improved sorghum technology package in the Maradi region of Niger. A propensity score matching method is used to address self-selection bias into the program. First, we estimate a propensity model to participate in the extension program, examine factors affecting the participation, and assess the average adoption effect on participants by testing for productivity difference between adopters and non-adopters. Secondly, we estimate a stochastic production technology frontier to compare technical efficiency of farmers in the extension program. We test for returns to scale, examine factors affecting technical efficiency of participants, and compare technical efficiency scores of participants based on their compliance to program recommendations.

Participants in the extension program are older, have less farming experience, and operate on larger farm sizes. After controlling for bias, there is very little change in the yield differences, which in both cases are substantial. There is some evidence for greater productivity of the smaller size producers.Technical efficiency of participants is increasing overtime, younger participants are technically more efficient and farming experience increases significantly participants' technical efficiency. Good followers of the fertilization technique recommendation are much more technically efficient.



**Keywords:** propensity score matching, stochastic frontier analysis, productivity, and efficiency.

## Introduction

To estimate the impact of new agricultural technologies the usual practice is to identify those adopting and not adopting to compare the mean differences. There are two problems with this approach. First, as in any extension program farmers do not always follow all the recommendations in particular complying to the agronomic recommendations. So, analysts need to separate the adopters following well the recommendations from other users of the new technologies.

Secondly, adopters are expected to have different characteristics than non-adopters. They may have better resources, more experience, greater access to outside resources, and more education. How much of the effects of these other factors are we attributing to the new technology difference? So, in this paper we try to separate these differences between adopters and non-adopters productivity by holding constant other factors besides the technology difference. Then we compare the differences in performance of participants according to how well they follow the program recommendations. Finally we compare the different groups for their differences with the efficiency frontier.

We first introduce the agricultural system in Niger and explain the sorghum technologies and the agricultural extension program. We then develop the methodology on propensity score matching for all producers in the sample and the stochastic frontier analysis for program producers in section three. We compare the differences in productivity of farmers in the extension program to non-participants by addressing self-selection bias of participation in the program by means of a propensity score matching (PSM) method. Using a stochastic frontier analysis (SFA) we identify the determinants of technical efficiency of good followers of the program recommendations to other participants. In section four, a description of the data and producers in the sample for both participants and non-participants is provided. In section five, we show the empirical model and variables used. We then present in section six the results followed by conclusions in section seven.

## Niger Agriculture

Low soil fertility, especially in N and P, is a fundamental problem resulting in low yields even with new cultivars in Sub-Saharan Africa (Sanchez, et al., 1997; Smaling, Nandwa, & Janssen, 1997; Sissoko & Breman, 1998). Moreover, the failure to replace the disappearing fallow system, which was the traditional method of restoring fertility with increased levels of inorganic fertilizers, means a further process of soil depletion. Every year, the magnitudes of soil nutrient losses between 1983 and 2000 in 37 African countries are estimated to be 4.4 million tons of N, 0.5 million tons of P and 3 million tons of K (Sanchez, et al., 1997; Smaling E. M., 1993; Smaling, Nandwa, & Janssen, 1997). These nutrient depletion rates correspond to 660 kg/ha, 75 kg/ha, and 450 kg/ha for respectively N, P, K (Sanchez, et al., 1997).

Historically, the land system use in Niger is extensive and the agricultural sector is characterized typically by few inputs outside of labor and the limited manure from own cattle or letting the nomadic herders graze on the stubble. Yet, increasing population has pressured agricultural lands to expand farming on low potential areas; shifting agriculture by extending farming onto marginal lands with naturally poor soil fertility and has resulted in food production at low and declining productivity levels.

Irregular rainfalls and price collapse discourage the substitution to inorganic fertilizer for the disappearance of the fallow systems. However, in spite of these obstacles studies in Burkina Faso and Mali have shown the profitability of new technologies combining moderate levels of inorganic fertilizers with new cultivars and improved agronomic techniques (Ibrahim Djido, Sanders, & Ouendeba, July 2012; Coulibaly J. , 2010; Abdoulaye, Sanders, & Ouendeba, 2008; Abdoulaye, Sanders, & Ouendeba, 2007; Coulibaly, Vitale, & Sanders, 1998; Shapiro & Sanders, 1998).

Moreover, other studies in Niger have found similar results of higher returns to inorganic fertilizers and demonstrated the possibility to obtain substantial yield increase from moderate inorganic fertilizers and new cultivars combined with improved agronomic practices (Abdoulaye, 2002; Adesina, Abbott, & Sanders, 1988; Abdoulaye & Sanders, 2006; Shapiro, Sanders, Reddy, & Baker, 1993; Baquedano & Sanders, 2006; Batiano, Christianson, Baethgen, & Mokwunye, 1992; Adesina & Sanders, 1991).

Missing from these studies is a matching technique to match producers adopting the technological package to otherwise comparable farmers still using the traditional technology holding constant observable characteristics. In many cases self-selection of farmers with particular characteristics could occur so that the yield and profit differences could partially reflect these self-selected differences as well as program effects. To separate these effects, adopters of the improved sorghum technological package can be compared to non-adopters with similar observable characteristics (Rosenbaum & Rubin, 1983). Also we then utilize a comparison of the groups in the program following well and not following well agronomic recommendations with the technical efficiency model.

The analysis is based upon actual field program introducing new sorghum technologies. This program is now in its 11th year in operation in the Sahel and is based here upon data for the last three years in Niger. The improved technology in Niger consists of a package of moderate level of inorganic fertilizers, improved sorghum cultivar (*Sepon 82*), fungicide and agronomic recommendations.

Users of the traditional sorghum technology employ the local sorghum cultivar, little inorganic fertilizer and their traditional farming techniques.[1]

**Methodological framework**

The first focus is to evaluate the average effect of the extension program on productivity for producers, who received the improved sorghum technology package holding constant recipients' observable characteristics and their resource features. In principle, the impact on productivity of the program is:

$$E(Y_1 - Y_0|Z, DV = 1) = E(Y_1|Z, DV = 1) - E(Y_0|Z, DV = 1) \quad \text{(Eq. 1)}$$

Where $E(.)$ is the expectation operator, $Y_1$ is the participants' yield for the improved sorghum, $Z$ is a vector of observable covariates containing farmers personal and their resource characteristics under the two technologies[2], $DV$ is a dummy variable taking one when the improved technology is adopted and zero otherwise, $Y_0$ is the yield participants could have realized had they not participated in the extension program. Both states of nature, $Y_1$ and $Y_0$, are not observable (Bravo-Ureta, Greene, & Solís, 2012; Imbens & Angrist, 1994; Heckman, Ichimura, & Todd, 1997). Since either the producer is a participant or not; therefore $E(Y_0|Z, DV = 1)$ is not readily available. So, assumptions need to be made to generate $E(Y_0|Z, DV = 1)$, the counterfactuals. One assumption for approximating $E(Y_0|Z, DV = 1)$ is to use outside farmers not members of the extension program $E(Y_0|Z, DV = 0)$ which often results in a bias equal to the difference

[1] Many of the traditional farmers employ small quantities of cowpeas with the sorghum and we are making a further adjustment to compare by revenue rather than yields so this is the first run of the model using the yield comparison.

[2] For all farmers using the two sorghum technologies the independent variables Z are not confounding variables (Rosenbaum & Rubin, 1983). This is referred to as "ignorable treatment assignment or unconfoundedness assumption" by Rosenbaum and Rubin (1983) or the "conditional independence assumption" by Lechner (1999).

$E(Y_0|Z, DV = 1) - E(Y_0|Z, DV = 0)$ (Mayen, Balagtas, & Alexander, 2010). Rosenbaum and Rubin (1983) show that one can use the propensity score to match participants to non-participants. In this way bias due to the characteristics identified is removed. This assumes that the assignment to the technology choice is independent of the outcomes given the observed covariates. Thus, $E(Y_0|Z, DV = 1) = E(Y_0|p(Z), DV = 0) = E(Y_0|p(Z))$ where $p(.)$ is the propensity or the likelihood of joining the extension program based on farmers' characteristics. This allows an unbiased estimation of the average productivity effect $E(Y_1 - Y_0|Z, DV = 1)$ of the extension program in Niger (Imbens & Angrist, 1994).

We adopt a three-step estimation method to evaluate the impact of the agricultural extension program on farmers' productivity and efficiency holding constant observable characteristics. In the first step, we estimate a probability model for the adoption of sorghum technological package to generate the propensity of being an adopter. In the second step, we use the predicted propensity scores. Matching is performed by pairing each participant in the program with one non-participant with similar observable characteristics captured in the propensity scores. After adopters have been matched to otherwise similar non-adopters the remaining observations are eliminated leaving a dataset of producers in the program and outside the program with more comparable characteristics (Nielsen & Sheffield, 2009). Then we test productivity differences between participants and non-participants.

In the third step the stochastic frontier model is estimated on the subset of producers. We estimate the production technology frontiers and the efficiency scores on the subset of farmers identified and then compare good followers of the agronomic recommendations to other participants.

*Determinants of program adoption*

The probability that farmer *i* adopts the new technology is a function of farmers' personal and farm characteristics.

$$P(adoption\ by\ farmer\ i) = f(farmers'personal\ charateristics, farm\ characteristics)$$

We will use a *probit* model to obtain predicted probabilities or predicted propensity scores of being a recipient of the improved sorghum technology package. The specification of the *probit* model is given by:

$$p(Z) = Prob(\vartheta_i = 1|Z) = Z_i'\alpha + \epsilon_i \qquad \text{(Eq. 2)}$$

Where $Prob$ is the probability function, $\vartheta$ is a dichotomous variable taking the value of zero if the farmer is using the traditional technology and the value of one if the farmer is using the improved technology of sorghum, $i$ indexes the farmer, $Z$ is a set of farmers' personal and their resource characteristics, $\alpha$ is a vector of parameters to be estimated using maximum likelihood estimation techniques, and $\varepsilon$ is a random error term normally distributed with mean zero and variance one such that $\epsilon \sim N(0,1)$.

*Propensity Score Matching (PSM)*

In practice, it is often problematic to match on high dimensional vector of covariates (Heckman, Ichimura, & Todd, 1997). Rosenbaum and Rubin (1983) demonstrate that matching farmers based on the propensity scores alone reduces what is called the curse of dimensionality. They also show that matching on this scalar limits the influence of farmers' and farm characteristics and is sufficient to remove bias due to these characteristics (Rosenbaum & Rubin, 1983). After matching on producers' propensity scores with similar economic and demographic characteristics, the increase in sorghum productivity is attributable to the extension program rather than these characteristics.

The propensity scores, the likelihood of adopting the improved sorghum technology package conditioned on observed covariates, have the virtue to balance the observed distribution of covariates across the two groups of sorghum technologies (Lee, 2008; Rosenbaum & Rubin, 1985) reducing dependence on covariates (Ho , Imai, King, & Stuart, 2007). This matching technique produces a group of producers still using the traditional sorghum technology and a group of the extension program members with similar attributes allowing a meaningful comparison of farmers. A difference in the outcomes of the matched two groups of farmers will be unbiased to estimate the average difference in productivity between the two sorghum technologies (Rosenbaum & Rubin, 1983; Heckman, Ichimura, & Todd, 1997).

We would want participants and non-participants to have the same values of $p(Z)$, the propensity scores, and the same probability distribution of $Z$, the observable covariates. This satisfies the balancing property of the propensity score meaning that the bias due to the covariates $Z$ has been controlled (Rosenbaum & Rubin, 1983). Moreover, if the difference in propensity scores between adopters and non-adopters is insignificant[3] then we will have more confidence in our matching (Dehejia & Wahba, 2002). A t-test can be conducted to test for statistical difference between the distribution of covariates $Z$ for adopters and non-adopters.

The matching algorithm to be utilized in this study will pair each participant, $DV = 1$, to non-participant, $DV = 0$, on the basis of their scores (Rosenbaum & Rubin, 1983). It is often difficult to find exact matches so we will match farmers using the nearest neighbor by pairing participants to non-participants with closest available propensity scores. In this matching algorithm a) members of the extension program and non-members are randomly ordered b) each participant is matched to another closest non-participant and then both are removed from the potential matching until all participants have been matched (Rosenbaum & Rubin, 1985). Members of the program that were not matched are eliminated from the dataset leaving more comparable farmers with similar characteristics (Nielsen & Sheffield, 2009).

*Comparisons with the stochastic frontier model*

We estimate the production possibility frontier functions (the improved technology' s frontier $PPF_1$ and the traditional' s frontier $PPF_2$) and identify factors associated with yield variation.

Yields may vary because of a lower productive technology (difference in PPFs) or a lesser technical efficiency (difference between observed output "A" and potential output "A*" on the PPF) or both (Mayen, Balagtas, & Alexander, 2010). We analyze the residuals to identify how far producers are from the PPF and compare their efficiency scores.

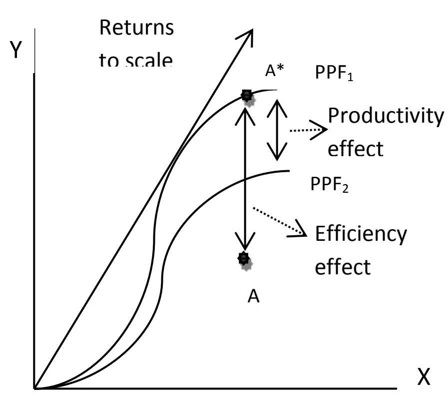


Figure 1. Difference in Productivity, Efficiency and Scales of Production

[3] If the balancing property is not satisfied (covariates are not balanced) then by "*proposition A*" of Rosenbaum and Rubin (1983) the propensity scores are poorly estimated and Dehejia and Wahba (2002) suggest adding additional (interaction or higher order) terms in the probability model.

With the residuals we separate the differences due to unobserved events (error measurement, chance) to individual farmers' inefficiency effects. Program participants are further investigated based on their compliance to agronomic recommendations by comparing the scores of good followers to those not following well the recommendations.

Various authors including Meeusen and van den Broeck (1977), Aigner, Lovell, and Schmidt (1977) and Battese and Corra (1977) suggested stochastic frontier analysis (SFA) to measure the technical efficiency of farmers. We will adopt the same techniques.

The proposed methodology for the stochastic frontier production function for a panel data is (as documented in Battese and Coelli, 1992; 1995; Kumbhakar and Lovell, 1989; 2000):

$Q_{it} = f(x_{it};\beta) * \exp(\varepsilon_{it})$ for i=1,.., T and t=1,…, T (Eq. 3)

where, the composed error is $\varepsilon_{it} = v_{it} - u_{it}$ (Eq. 4)

$Q_{it} = f(x_{it};\beta) * \exp(v_{it} - u_{it})$ (Eq. 5)

$$Q_{it} = \underbrace{f(x_{it};\beta)}_{\text{Deterministic component}} * \underbrace{\exp(v_{it})}_{\text{Noise component}} * \underbrace{\exp(-u_{it})}_{\text{Inefficiency component}} \quad \text{(Eq. 6)}$$

Where i denotes the farmer and t the year, $Q_{it}$ represents output produced (sorghum) by the i$^{th}$ farmer in year t, $f(x_{it};\beta) * \exp(v_{it})$ is the stochastic production frontier composed of a deterministic piece $f(x_{it};\beta)$ common to all farmers, and farmers' specific random error component $\exp(v_{it})$ to account for statistical noise, $x_{it}$is a (1 x k) known input vector involved in the production process associated with the i$^{th}$ farmer in year t, β is a (k x 1) represents the vector of unknown technology parameters to be estimated, $v_{it}$ is a two-sided statistical noise component such that $v_{it} \sim iid\ N(0, \sigma_v^2)$. Statistical noise encompasses sources of error measurement in econometric estimations including omission of relevant variables in the right hand side of the relationship and errors from the choice of a functional form. We assume $v_{it}$ to be independently distributed of the one-sided inefficiency component $u_{it}$. $u_{it}$ associated with inefficiency effects is assumed to be independent of $v_{it}$, non-negative, such that $u_{it} \sim iid\ N^+(\mu = z_{it}\delta, \sigma_u^2)$ are non-negative truncated at zero of the normal distribution with mean $\mu = z_{it}\delta$ as a function of a set of explanatory variables $z_{it}$ and $\sigma_u^2$ a constant variance[4]. The $\varepsilon_{it}$, the composed error term, is thus asymmetric since $v_{it}$ is two-sided and $u_{it}$ is non-negative.

[4] In Greene's (1993) point of view, the nature of the stochastic frontier to measure technical efficiency is that farmers' inefficiency is a shock that is homogeneously distributed across farmers. This assumption could be relaxed

In this framework, the objective is to estimate the production technology parameters, the βs, and also the individual farmers technical inefficiency levels, the $\delta s$. This implies a separation of the inefficiency effects $u_{it}$ from the statistical noise $v_{it}$ in the composed error term $\varepsilon_{it}$for each farmer. The inefficiency effects[5], $u_{it}$, in the stochastic frontier model (Eq. 5) can be expressed as:

$$u_{it} = z_{it}\delta + w_{it} \tag{Eq. 7}$$

Where $z_{it}$is a (1 x m) vector of independent variables that are assumed to influence farmers' level of efficiency. This efficiency level varies over time and defines an index of technical inefficiency. $\boldsymbol{\delta}$ is a (m x 1) vector of unknown parameters to be estimated associated with the set of explanatory variables in the inefficiency model. The $w_{it}$is an error term assumed to be independently truncated at $-z_{it}\delta$ of the normal distribution with mean zero and variance $\sigma_u^2$ . $w_{it}{\sim}N(0, \sigma_u^2)$ is consistent with the assumption that $u_{it} \geq 0$ and $u_{it}{\sim}iid\ N(z_{it}\delta, \sigma_u^2)$.

Farmers' specific TE is given by the ratio of observed output to the corresponding efficient output on the frontier production function.

$$TE_{it} = \frac{Q_{it}}{Q_{it}^*} = \frac{Q_{it}}{f(x_{it};\beta)*\exp(v_{it})} = \frac{E[Q_{it}/u_{it},x_{it}]}{E[Q_{it}/u_{it}=0, x_{it}]} = \exp(-u_{it}) = \exp(-z_{it}\delta - w_{it}) \tag{Eq. 8}$$

The specification (Eq. 8) allows for TE to vary across farmers and over time. The level of efficiency is in the interval of zero to one since the $u_{it}$s are assumed to be non-negative. A farmer with TE=1 when $u = 0$ is efficient while all other farmers are inefficient for not achieving the maximum producible output on the production frontier. TE measures the production level of a farmer relative to a level of production that could be produced by a fully efficient farmer who is using the same technology or input combination.

*<u>Summary of methodologies</u>*

The steps can be summarized as follows: a) run a probit regression model to estimate the propensity scores such that the probability of adopting the new technology is a function of farmers personal and their farm (in this case assets') characteristics; b) order farmers based on their propensity scores c) match each participants to non-participants using nearest matching

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to allow for a more complex formulation of the stochastic frontier by allowing mean and variance inefficiency to vary across farmers and therefore be heterogeneous (Greene, 1993). For the sake of simplicity and without affecting results we believe this assumption of homogeneity is fair.

[5] Following Battesse and Coelli (1992) model of time varying inefficiency the technical inefficiency model takes the form of $u_{it} = f(t).u_i = \exp[\eta\ (t - T)]$ where $f(t)$determines the time dependent technical efficiency.

without replacement;[6] d) test for productivity differences; and e) estimate a stochastic frontier model testing efficiency effect and returns to scale.

## Data and description of variables

*Data-Panel Data*

This study uses primary field work data collected over three years in the Maradi region of Niger on a random sample of 44 members of the extension program and 185 farmers outside the program. A balanced three year panel data of 132 (44*3) farmers was constructed on participants and an unbalanced three year panel data was collected on 562 producers using the traditional technology for the 2010-2011-2012 crop years.

When applied to panel data in which the unit of analysis is the panel of observations rather than the observations, standard matching techniques lead to double dimensionality issues[7] (Nielsen & Sheffield, 2009). Matching on the correct unit of analysis captures time trends information allowing the creation of better matches than in standard observation level matching techniques.

Nielsen and Sheffield (2009) examine some of the strategies proposed in the literature to avoid the problems. Two strategies are adopted here. Ward and Bakke (2005) propose to ignore the problem while Young (2008) proposes to do the matching between participants to non-participants by year (Ward & Bakke, 2005; Young, 2008). This allows testing of productivity difference for the pooled sample and by year.

*Description of variables and summary statistics*

The observable characteristics, Z, for the Probit adoption model to explain the adoption patterns of new sorghum technologies among smallholder farmers in Niger are the age of the farmer , the educational level of the farmer in years of schooling, the experience of the farmer given by the number of years of farming independently, the agricultural assets measured by the total land area for all types of crops, the ownership of a traditional plow equipment, the ownership of a cart, and the number of livestock (camels, cows, lambs, goats) owned by the farmer.

The inputs of the production function are the conventional factors of production land, annualized capital costs and labor. Information on sorghum land area is readily available; the

[6] This also involves testing the balancing property.

[7] Matching on a panel of data by pruning unmatched observations creates missing data in the panel structure in which observations are linked to each other (Nielsen & Sheffield, 2009).

ownership of equipment, carts and the livestock size measure farmer's capital; labor is measured by the average number of days of family and hired labor used during the crop production process. Additional inputs are the quantity of inorganic fertilizers applied and the number of carts of manure provided in the field. The outcome of analysis is output of sorghum produced by farmers in the analysis.

Farmers using the traditional sorghum technology have less farming experience, possess fewer land assets, own more carts and plows, apply more manure fertilizer per ha, use less labor per ha and obtained lower yields than participants of the extension program (table 1). With no statistical significance, traditional farmers are younger, less educated, hold more livestock, and apply less inorganic fertilizer per ha than participants (table 1).

Table 1. Farmers' characteristics, capital resources and factors of production

| Variables | Description and units of the variable | Average under traditional technology (TT) | Average under improved technology (IT) | TT compared to IT farmers | T-Test of mean difference between TT and IT |
|---|---|---|---|---|---|
| | Farmers' personal characteristics | | | | |
| *Age* | Years | 47.51 | 52.25 | Younger | Insignificant |
| *Education* | Years | 2.10 | 2.36 | Less educated | Insignificant |
| *YearsFarming* | Years | 27.16 | 30.60 | Less experience | Significant |
| | Land assets and capital | | | | |
| *FarmSize* | Ha | 4.12 | 4.57 | Less land assets | Significant |
| *OwnershipCarts* | 1 if owned and 0 otherwise | 55.34% owned a cart | 50.76% owned a cart | Owned more carts | Significant |
| *OwnershipEquipment* | 1 if owned and 0 otherwise | 66.01% owned a plow | 64.39% owned a plow | Owned more plows | Significant |
| *Livestock* | Number of heads of cattle, goats and lambs | 7.39 | 6.87 | More livestock | Insignificant |
| | Other factors of production | | | | |
| *ManureHa* | Number of carts/Ha | 7.04 | 6.87 | Apply more manure | Significant |
| *InorganicFertilizerHa* | Kg/Ha | 27.52 | 92.45 | Apply less inorganic fertilizer | Insignificant |
| *LaborHa* | Man day per ha | 22.18 | 30.88 | Less labor | Significant |

| | Outcome of comparison under the two technologies | | | | |
|---|---|---|---|---|---|
| *Yield*[a] | Kg/ha | 682 | 1,409 | Half yield | Significant |

[a] Sepon 82 yields in 2012, 2011, and 2010 are respectively 1,257, 1,352, and 1,618 kg/ha. The traditional sorghum cultivar yields in 2012, 2011, and 2010 are respectively 685, 674, and 686 kg/ha.

*Source: 2013 authors' farm household surveys*

**Empirical model**

The probit adoption model is given by:

$$p(Z) = Prob(\vartheta_i = 1|Z) = \alpha_0 + \sum_{i=1}^{8} \alpha_i * Z_i + \epsilon_i = \alpha_0 + \alpha_1.Age + \alpha_2.AgeSqr + \alpha_3.Education + \alpha_4.YearsFarming + \alpha_5.FarmSize + \alpha_6.OwnershipCarts + \alpha_7.OwnershipEquipment + \alpha_8.Livestock + \epsilon_i$$

The Cobb-Douglas functional form is assumed for the stochastic frontier model given by:

$$logQ_{it} = \beta_0 + \beta_1.\log(Area_{it}) + \beta_2.\log(CapitalCost_{it}) + \beta_3.\log(Manure_{it}) + \beta_4.\log(InorganicFertilizers_{it}) + \beta_1.\log(Labor_{it}) + \beta_t.t + v_{it} - u_{it}$$

And the inefficiency model is given by:

$$u_{it} = \delta_0 + \delta_1.Age_{it} + \delta_2.AgeSqr_{it} + \delta_3.Education_{it} + \delta_4.YearsFarming_{it} + \delta_5.YearsFarmingAge_{it} + \delta_6.PropArea_{it} + \delta_t.t + w_{it}$$

Where *Age*, *Education*, *YearsFarming*, *FarmSize*, *OwnershipCarts*, *OwnershipEquipment* and *Livestock* are as previously defined. *AgeSqr* is the square of the age variable, *Area* is the size of operation of the sorghum technology, *CapitalCost*[8] is the combined annualized capital cost of carts, equipment and livestock, *Manure* is the number of carts of manure applied in the sorghum field, *InorganicFertilizers* is the quantity in kg of inorganic fertilizers applied in the sorghum field, *Labor* is the number of man days working in the field, *YearsFarmingAge* is an interaction term between *YearsFarming* and *Age* variables, and *PropArea* is the proportion of the total area under the sorghum technology.

**Results and Discussion**

*The probit adoption model (table 2)*

[8] We applied a 10% depreciation rate on carts and plows over the three years.

Four variables were significant in explaining participation in the extension program: *Age, AgeSqr, YearsFarming,* and *FarmSize*. This model shows three major findings: adopters of the improved sorghum technology are older, have less farming experience, and operate on larger farm size.

There is a positive relationship between program participation and age. This implies that there is a higher likelihood for older farmers to adopt the improved sorghum technology but at a decreasing rate over the higher ages. This finding is in contrast with previous studies that have documented how operator age is associated with less adoption (Mayen, Balagtas, & Alexander, 2010; Gould, Saupe, & Klemme, 1989; D'Souza, Cyphers, & Phipps, 1993). Farming experience, the number of years farming independently, came out to be negatively related to program participation. Less experienced farmers are more likely to adopt the improved sorghum technology. This finding is consistent with previous literature on adoption of new technologies (Foster & Rosenzweig, 1995; Cameron, 1999; Ervin & Ervin, 1982).

Combining the two findings that older and the less experienced farmers are more likely to adopt the new sorghum technology might seem contradictory. Older farmers have been around more and if they have less years of experience they were involved in activities outside the farm. This outside activity would be expected to instill more confidence in these new sources of information from the new program. The program is associated with the federal agricultural research service (INRAN) so those with more outside experience would be more familiar with this agency.

There is a positive correlation between total crop acres farmed, *FarmSize*, and the extension program participation. Our results suggest that producers with larger farm size will choose the extension program. Similar results of the positive effect of farm size on new technology adoption were found in other studies (Belknap & Saupe, 1988; Gould, Saupe, & Klemme, 1989; Rahm & Huffman, 1984).

The next step is to compute the predicted propensity scores of being a member of the extension program. The scores will be used to match farmers with similar characteristics to compare the impact of the program on farmers' productivity.

Table 2. Estimates of the probit adoption model

| Variables | Variable description | Coefficients | Standard Errors |
|---|---|---|---|
| *Constant* | Intercept | -5.117*** | 1.364 |
| *Age* | Producer's age | 0.231*** | 0.082 |

| | | | |
|---|---|---|---|
| *AgeSqr* | Producer's age squared | -0.003** | 0.001 |
| *Education* | Years of schooling | 0.015 | 0.015 |
| *YearsFarming* | Years of farming experience | -0.162*** | 0.056 |
| *FarmSize* | Total land holding | 0.040* | 0.021 |
| *Carts1 (Yes)* | Ownership of carts | 0.174 | 0.148 |
| *Equipment1 (Yes)* | Ownership of plows | -0.014 | 0.155 |
| *Livestock* | Livestock size | -0.006 | 0.006 |
| Number of Observations = 634 | | | |
| Pseudo R2 = 0.451 | | | |

*,**,*** significance levels at 10%, 5% and 1% respectively.

*Source: 2013 authors' farm household surveys*

*The PSM (table 3)*

We use the single nearest neighbor matching algorithm to pair participants to non-participants with most identical propensity scores. Table 3 displays the mean differences of observables characteristics used in the probit model between the two sorghum technologies, the percent bias of the matched and unmatched sample and the percent reduction in bias after completion of the matching algorithm.

After controlling for bias there is a better balance in the matched sample for most of the covariates. We would want the *%bias* after matching for each covariate and the mean absolute bias to be less than 5%. Only one variable, *Livestock,* did not satisfy this criterion but the absolute mean bias of 4.8% after matching validates the balancing property. Adopters and non-adopters with nearest scores and similar characteristics have been successfully matched.

Table 3. Mean differences in covariates before and after matching

| Variable | Sample | Mean participants | Mean non-participants | %bias | %reduction bias |
|---|---|---|---|---|---|
| *Age* | Unmatched | 52.25 | 47.75 | 32.9 | |
| | Matched | 52.35 | 52.37 | -0.1 | 99.7 |
| *Agesqr* | Unmatched | 2919.10 | 2462.90 | 31.1 | |
| | Matched | 2929.70 | 2916.10 | 0.9 | 97 |
| *Education* | Unmatched | 2.36 | 2.07 | 7.9 | |
| | Matched | 2.33 | 2.30 | 0.8 | 89.4 |
| *YearsFarming* | Unmatched | 30.60 | 27.35 | 21.9 | |
| | Matched | 30.79 | 31.23 | -3 | 86.4 |
| *FarmSize* | Unmatched | 4.57 | 4.12 | 25.1 | |
| | Matched | 4.51 | 5.06 | -0.7 | -21.3 |
| *Carts1* | Unmatched | 0.49 | 0.45 | 13.8 | |
| | Matched | 0.49 | 0.47 | -16.7 | 45.8 |
| *Equipment1* | Unmatched | 0.36 | 0.34 | 8.4 | |
| | Matched | 0.36 | 0.33 | 4.6 | -98 |

| | | | | | |
|---|---|---|---|---|---|
| *Livestock* | Unmatched | 6.87 | 7.44 | 3.2 | |
| | Matched | 6.84 | 8.01 | 6.4 | -102.7 |

Note: The mean bias before and after matching are respectively16.6% and 4.8% (<5%).
*Source: 2013 authors' farm household surveys*

*Difference in productivity (table 4)*

The extension program has a big impact on farmers' yields. The yield differences between participants and non-participants before and after controlling for bias are respectively 727 kg/ha and 718 kg/ha.

These important findings indicate that there is very little yield difference correction after adjusting for the characteristics. The yield differences are large and continue to be large even holding farmer and farm characteristics constant. The observed impact of the extension program on productivity reflects largely the success of the improved sorghum technological package in the region,the improved cultivar *Sepon 82* plus inorganic fertilizers plus fungicides and training[9].

Table 4. Unbiased estimate of the extension program effect on yields (ATT)

| Sorghum yield | Sample | Treated | Controls | Difference | S.E. | T-stat |
|---|---|---|---|---|---|---|
| | Unmatched | 1,409 | 682 | 727 | 45 | 16.2 |
| Pooled | ATT* | 1,412 | 694 | 718 | 67 | 10.8 |
| | Unmatched | 1,257 | 686 | 571 | 70 | 8.2 |
| 2012 | ATT | 1,263 | 708 | 555 | 101 | 5.5 |
| | Unmatched | 1,352 | 674 | 678 | 80 | 8.5 |
| 2011 | ATT | 1,401 | 711 | 690 | 126 | 5.5 |
| | Unmatched | 1,618 | 685 | 933 | 80 | 11.6 |
| 2010 | ATT | 1,649 | 659 | 989 | 116 | 8.6 |

*ATT Average treatment effect on the treated
Note: S.E. does not take into account that the propensity score is estimated.
*Source: 2013 authors' farm household surveys*

*The stochastic frontier model (table 5)*

Since participants of the extension program were found to be more productive (table 5), we estimate the production technologies separately for the two groups of farmers. Here we focus on program participants' differences by estimating a frontier model. We will investigate factors that affect production of the improved technology and test the returns to scales. We then examine participants' performance based on their compliance to program recommendations by comparing

[9] One critical component of the program is access to input credit at favorable terms. We return to this issue in the conclusions.

their technical efficiency scores. The performance of adopters of the improved technology package will be assessed by investigating how well they follow the most critical agronomic recommendation side-dressing inorganic fertilizers by adults as opposed to broadcasting and letting the children do the fertilization.

Three variables are significant in the stochastic production frontier model. The coefficient on *LogArea* and *LogInorganicFertilizers* are significant and less than one. This suggests that sorghum output increases by 0.698% (0.069%) if the size of operation (inorganic fertilizer) is increased by 1%.We were disappointed by the negative time trend but this was a very short period and many factors could be responsible.

Returns to scale are calculated by summing the elasticities for the inputs in table 5. The test consists of testing whether the sum of parameters of production is equal to, less than or greater than one for constant returns to scales (CRTS), decreasing returns to scales (DRTS) and increasing returns to scales (IRTS) respectively. The significant decreasing returns to scale appears to reflect the greater ability of the small farmers to produce a technology with intensive labor requirements including thinning and more cultivation at the appropriate times.

In addition, the output from the frontier estimation provides *Sigma_u2* the variance due to farmers' inefficiency effects, S*igma_v2* the variance due to random effects, *Sigma2* (=*sigma_u2* + *sigma_v2)* the total variance, *gamma* the ratio of the farmer specific variability (*sigma_u2)* to total variance (*sigma2)*, *Mu* the mean of the truncated normal distribution and *Eta* the time varying effect.

The significant positive sign on the *Eta* coefficient implies that technical efficiency is increasing overtime which is what we would expect after years of training. The *gamma* parameter in the all program farmers' regression is large (0.549) and is significantly different from zero. This means that farmers' inefficiency effects play an important role in explaining failure to achieve maximum output.

Table 5. Random effects maximum likelihood estimates of the SFA

| Variables | Coef. | Std. Err. | 95% Conf. Interval | |
|---|---|---|---|---|
| *Constant* | 8.338*** | 0.730 | 6.907 | 9.769 |
| *LogArea* | 0.698*** | 0.110 | 0.481 | 0.914 |
| *LogCapitalCost* | -0.073 | 0.054 | -0.178 | 0.033 |
| *LogManure* | -0.017 | 0.012 | -0.041 | 0.007 |
| *LogInorganicFertilizers* | 0.069*** | 0.025 | 0.020 | 0.118 |
| *LogLabor* | 0.108 | 0.102 | -0.091 | 0.307 |

| | | | | |
|---|---|---|---|---|
| *LogYear* | -0.508*** | 0.157 | -0.815 | -0.201 |
| *Mu* | 0.522* | 0.299 | -0.064 | 1.108 |
| *Eta* | 0.234* | 0.130 | -0.021 | 0.489 |
| *Sigma2* | 0.083 | 0.025 | 0.046 | 0.150 |
| *Gamma* | 0.549 | 0.185 | 0.220 | 0.841 |
| *Sigma_u2* | 0.046 | 0.027 | -0.006 | 0.098 |
| *Sigma_v2* | 0.037 | 0.011 | 0.015 | 0.060 |

*,**,*** significance levels at 10%, 5% and 1% respectively.
*Source: 2013 authors' farm household surveys*

*Technical inefficiency effect (tables 6 and 7)*

Participants' age is associated with lower efficiency. Younger farmers are technically more efficient than older participating in the extension program. Farming experience increases significantly farmers' technical efficiency but the negative sign on *YearsFarmAge* suggests that older participants with more farming experience are being less efficient. One possible explanation is the time it takes to fully convince older farmers to follow the program recommendations is longer. So, the uptake and assimilation of these technologies may be faster among younger farmers with less farming experience. Overtime, these farmers' efficiency will increase even faster than in the more advanced group. The positive sign carried by the *Year* parameter is in line with the increasing efficiency level of farmers overtime shown previously in table 5 (positive sign on *Eta*). Members of the program planting a large proportion of their land to the improved sorghum technology are also found to be more efficient.

Table 6. Factors affecting TE for the improved sorghum technology

| Variables | Coef. | Std. Err. | 95% Conf. Interval | |
|---|---|---|---|---|
| *Constant* | 0.524*** | 0.0561 | 0.4138 | 0.6336 |
| *Age* | -0.003** | 0.0012 | -0.0052 | -0.0005 |
| *Education* | -0.003 | 0.0028 | -0.0087 | 0.0024 |
| *YearsFarming* | 0.004* | 0.0019 | -0.0001 | 0.0074 |
| *YearsFarmingAge* | -0.0001* | 0.00003 | -0.0001 | 0.00001 |
| *PropArea* | 0.222*** | 0.0698 | 0.0849 | 0.3587 |
| *Year* | 0.076*** | 0.0038 | 0.0686 | 0.0836 |

*,**,*** significance levels at 10%, 5% and 1% respectively.
*Source: 2013 authors' farm household surveys*

The technical efficiency scores of participants vary between 40% and 87% with a mean of 60% (table 7). But not all farmers participating in the extension program follow the agronomic recommendations. The compliance to fertilization methods, sidedressing done by adults rather than broadcasting or kids applying the fertilization, is one of the most critical agronomic factor that the program has recommended participants to follow. The scores of good followers of this recommendation varied between 51% and 87% with an average technical efficiency index of 69% higher than the mean score of when the recommendation is neglected (table 7). This suggests that in order to increase the yield response to inorganic fertilizers farmers' efficiency should be improved by better fertilization technique. This seems to be an agronomic recommendation that can be implemented with extension or other training. Elsewhere the yield decline of 300 to 500 kg/ha was frequently found by the wrong application method (Ibrahim Djido, Sanders, & Ouendeba, July 2012). From an extension standpoint, this aspect will be reinforced.

Table 7. Compliance to fertilization technique and technical efficiency scores

| | | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Overall participants | | 60% | 0.13 | 40% | 87% |
| Sidedressing done by Adults | Complied | 69% | 0.14 | 51% | 87% |
| | Did not comply | 57% | 0.09 | 51% | 67% |

*Source: 2013 authors' farm household surveys*

**Conclusion**

The impact of the extension program on farmers' yield is substantial in Niger. Even after holding constant farmers' characteristics the productivity in the program still doubles the traditional technology. Results from field work reflect amply the unbiased productivity difference estimated using the propensity score matching in this analysis.

Within the program, participants applying correctly the inorganic fertilizer, side-dressing done by adults, are more efficient and more attention will be given to this group of farmers to further expand their outputs. Participants not following the agronomic fertilization technique will be given more training to move toward a better efficiency level.

Elsewhere we have shown the profitability of the new technology taking into account the increased input requirements (Ibrahim Djido, Sanders, & Ouendeba, July 2012; Coulibaly J. , 2010; Abdoulaye, Sanders, & Ouendeba, 2008) even without doubling the yields as has occurred with the best program performers. Even taking into account risk as the other studies cited above have done, this field work and quantitative analysis suggest moving to moderate fertilizer recommendations with the improved technology components rather than continuing the low input and micro fertilization techniques often being recommended for sorghum in the Sahel.

In the pilot projects in four countries including Niger, input credit was provided because combining input increases and bank loans were considered major changes before we could confirm the productivity and profitability effects of the new technologies. Now that this has been confirmed and scaling up has occurred in both Mali (an estimated 10,000 ha in the sorghum and millet improved activities in 2012) and Senegal. This scaling up is beginning in Burkina Faso; in 2013 we will devote more attention to the ability of farmers and farmers' associations to obtain input credits. Some farmers have self-financed and banks' conditions and requirements have varied. Credit has also been obtained from input suppliers and a large millet food processor in Senegal. So clearly we can look at the credit factor in the scaling up process in the future.

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