Feed the Future Innovation Lab for Food Security Policy

Research Paper #172 May 2020

Mali Food Security Policy Research Program

EFFECTS OF THE FERTILIZER SUBSIDY PROGRAM ON FERTILIZER USE, FARM PRODUCTIVITY AND CROP SALES IN MALI

By

Melinda Smale, Amidou Assima, Véronique Thériault, Yénizié Kone

Food Security Policy *Research Papers*

This *Research Paper* series is designed to timely disseminate research and policy analytical outputs generated by the USAID funded Feed the Future Innovation Lab for Food Security Policy (FSP) and its Associate Awards. The FSP project is managed by the Food Security Group (FSG) of the Department of Agricultural, Food, and Resource Economics (AFRE) at Michigan State University (MSU), and implemented in partnership with the International Food Policy Research Institute (IFPRI) and the University of Pretoria (UP). Together, the MSU-IFPRI-UP consortium works with governments, researchers and private sector stakeholders in Feed the Future focus countries in Africa and Asia to increase agricultural productivity, improve dietary diversity and build greater resilience to challenges like climate change that affect livelihoods.

The papers are aimed at researchers, policy makers, donor agencies, educators, and international development practitioners. Selected papers will be translated into French, Portuguese, or other languages.

Copies of all FSP Research Papers and Policy Briefs are freely downloadable in pdf format from the following Web site: https://www.canr.msu.edu/fsp/publications/

Copies of all FSP papers and briefs are also submitted to the USAID Development Experience Clearing House (DEC) at: http://dec.usaid.gov/

AUTHORS

Melinda Smale is a Professor in the Department of Agriculture, Food and Resource Economics, Michigan State University.

Amidou Assima is a Statistician/Economist with the Projet de Recherche sur les Politiques de Sécurité Alimentaire au Mali (PRePoSAM), Bamako, Mali.

Véronique Thériault is an Associate Professor in the Department of Agriculture, Food and Resource Economics, Michigan State University

Yénizié Kone is Director of MSU's Regional Office in Bamako, Coordinator of the Projet de Recherche sur les Politiques de Sécurité Alimentaire au Mali (PRePoSAM).

AUTHORS' ACKNOWLEDGEMENT

This study was funded by USAID/Mali under the project titled "Projet de recherche sur les politiques de sécurité alimentaire au Mali (PRePoSAM)" awarded under the Food Security Innovation Lab's Cooperative Agreement Number AID-688-A-16-00001. The authors alone assume responsibility for any remaining errors of fact or interpretation.

The authors wish to thank the team of field supervisors and enumerators at the Institut d'Economie Rurale (IER) Programme Economie des Filières for the care and professionalism they exhibited in conducting four rounds of detailed farm household surveys as well as village-level focus groups. They gratefully acknowledge field supervision of Naman Keita, research coordinator for PRePoSAM, and Alpha Kergna, senior economist, Economie des filières (ECOFIL) program of the l'Institut d'Economie Rurale (IER), Bamako, Mali.

Authorship attribution: Smale (conceptualization, statistical analysis, writing, editing; Assima (statistical analysis, writing, editing, data curation); Theriault (conceptualization, writing, editing), Kone (policy history and implications).

This study is made possible by the generous support of the American people through the United States Agency for International Development (USAID) under the Feed the Future initiative. The contents are the responsibility of the study authors and do not necessarily reflect the views of USAID or the United States Government

Published by the Department of Agricultural, Food, and Resource Economics, Michigan State University, Justin S. Morrill Hall of Agriculture, 446 West Circle Dr., Room 202, East Lansing, Michigan 48824, USA

SUMMARY

Mali's most recent phase of fertilizer subsidies began during the global food crisis of 2008/09, but there is little evidence-based information concerning its effects. To generate information of potential use to policymakers in Mali, we implemented a survey to a random sample of 2400 extended farm family households in two major agroecological zones of Mali—the Delta du Niger and the Plateau de Koutiala.

In this paper, we test the effects of the fertilizer subsidy on total fertilizer applied, yield, target crop income and quantity of all crops sold. We find that subsidized fertilizer accounts for most of the total fertilizer applied by farmers, suggesting that in some instances it is displacing demand for commercial fertilizer. Average fertilizer use rates in kgs appear to be below the recommended quantities for all target crops, despite subsidy receipts. In future research, we intend to verify these findings converting units to nitrogen nutrient kgs, which standardizes across fertilizer types and permits a more exact comparison.

We compare regression results across several econometric approaches to improve their reliability. Each econometric approach provides evidence that considering all crops combined, the fertilizer subsidy has a positive effect on total fertilizer applied per ha, yields, and crop revenues of target crop, as well as on quantities of all crops sold. However, important differences are observable among crops. On average, subsidy effects on millet and sorghum outcome variable were weak or not statistically significant. Average subsidy effects on all outcome variables were strong for rice. Average subsidy effects were strong on maize yields, but not revenues or sales of other crops. For cotton, the subsidy only allowed an increase in the mean quantities of fertilizers used without improving productivity or other outcomes.

The dose-response estimation suggests efficiency intervals in which the fertilizer subsidy has a positive marginal effect on fertilizer use, productivity and crop sales. These also vary from one crop to another, but are estimated only for rice, maize and cotton given that mean effects are not significant for sorghum and millet. We find no positive marginal effect of subsidized fertilizer on yields below 65 kg/ha for rice and 87 kg/ha for maize. The graphs also show peaks at high levels of subsidized fertilizer for both crops, with declining marginal returns after that point. For rice, marginal effects on rice revenues have a similar shape to that of the yield effect, and effects on quantities of all crops sold are strong through much of the range of subsidized fertilizer applied in the data. This last result is observable also for maize at higher levels of the subsidy, suggesting some spillovers from rice and maize to non-target crops. No positive effect on cotton yields, cotton revenues or quantities of all crops sold is discernible regardless of the level of subsidization.

The fertilizer subsidy in Mali is currently designed to target particular crops and enhance their productivity. We conclude that the design could be made more efficient by either reconsidering target crops or targeting the subsidy according to different criteria. We consider that applying the subsidy to cotton represents a deadweight loss—that is, a public expenditure that leads to no discernible supply shift. This last finding could be season-dependent, or result from factors we could not measure in this analysis—such as cotton seed quality.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Over the last decade, numerous sub-Saharan African countries, including Mali, have established a new generation of agricultural input subsidies with the goal of promoting adoption, increasing productivity and contributing to national food security. A substantial body of literature analyzes the impacts of this 'second generation' of fertilizer subsidy programs on various farm-level outcomes in Eastern and Southern Africa. Detailed reviews of the impacts analyses are found in Druilhe and Barreiro-Hurlé (2012), Wanzala-Mlobela et al. (2013), Kato and Greeley (2016) and Jayne et al. (2018), and Smale and Thériault (2019). Recently, Holden (2019) concluded that these programs suffer from major design and implementation failures, falling short of the market-smart principles originally envisaged by Morris et al. (2007).

Following the global food crisis of 2007/08, the Malian government launched a program called *Initiative Riz*. The program aimed to boost rice production and productivity through use of subsidized fertilizer. Although the program had limited success (Smale, Diakité and Keita 2011), the government continued it and subsequently included additional crops. Building on the long-term state subsidy benefiting cotton (Kone et al. 2019a), cotton farmers were added first. After gold, cotton is the second source of export revenues. Maize, which was originally promoted as a rotation crop with cotton in response to concerns for household food security among cotton growers, was subsequently added. In recent years, maize has been gaining in popularity as a staple food and animal feed, but only grows in higher rainfall areas. The principal starchy staples, sorghum and millet, were subsequently added to the list of eligible crops. Wheat growers also benefit from the subsidy, although area planted to this crop in Mali is estimated at under 1% of all area planted to cereal crops (FAOSTAT 2020). Other crops, such as grain legumes, are not eligible to receive subsidized fertilizer. Another recent change is the piloting of an electronic voucher program, which was introduced in 2016/17 with the aim of increasing efficiency and transparency in the fertilizer subsidy program (Kone et al. 2019a). Our initial evidence regarding the pilot program was not promising (Kone et al. 2019b).

Fertilizer subsidies are now the largest expense item in government spending on rural development in Mali. The amount spent by the government on subsidized fertilizer varies greatly from year to year, but shows an upward trend. The amount went from 11.6 billion FCFA in 2008 to nearly 36.7 billion FCFA in 2017, an increase of more than 215%. The average annual expenditure on fertilizer subsidies over the last ten years represents nearly 17% of the agricultural budget and 2% of national budget (Thériault et al. 2018a).

As currently designed, all Malian farmers of target crops may obtain subsidized fertilizer at a quantity that is proportional to the number of hectares devoted to those target crops. Further, while all of the crops targeted by the subsidy program play key roles in the socio-economic development of Mali. Yet, according to the latest manual of procedures (MA 2019), subsidized fertilizer as a share of recommended application rates per ha varies by crop and overtly favors fully-controlled irrigated rice maize (100%) and cotton over sorghum and millet (35%). Figures were confirmed to be the same during the period of our survey (A. Niangado, DNA, May 25, 2020). One explanation for differential subsidies is that fertilizer response rates are considered to be lower for sorghum and millet than for these other crops. Our econometric analyses on this project have shown fertilizer response rates that are within the range reported in the literature but confirmed that response rates are lower for sorghum than for maize on the Plateau de Koutiala (Haider et al. 2018).

Despite that the current fertilizer subsidy in Mali has been in place for over a decade, we found only a few impact studies. To address the paucity of statistical information about the impact of the fertilizer subsidy program in Mali, we implemented a survey with a random sample of 2400 extended farm family households in two major agroecological zones of Mali—the Delta du Niger and the Plateau de Koutiala. Households were clustered by enumeration sections (SEs) and stratified by form of delivery of the fertilizer subsidy (electronic vs paper voucher, known as *caution technique*) and extension structure (highly structured vs less structured systems).

In preliminary analysis of the data we collected, Haggblade et al. (2019) found that while more than 80% of farmers interviewed received some fertilizer through the national program, rates were 10% to 20% higher in areas served by the Office du Niger (ON) and the CMDT compared to the unstructured extension zones serviced by the Directions Régionales d'Agriculture (DRA). During the 2017/18 season, efforts to reform Mali's fertilizer subsidy system through the introduction of e-voucher pilot program operated on a very small scale (Kone et al. 2019). Across the 60 villages we surveyed where the e-voucher was piloted, farmers received most of their subsidized fertilizer through the original system of paper vouchers. Paper vouchers accounted for 78% of quantity of subsidized fertilizer received by Delta farmers and for 95% in the Plateau (Haggblade et al. 2019).

In two previous studies, we have employed this dataset to explore some of the impacts of the subsidy program on dietary intake, which is one component of nutrition. Smale et al. (2019) examined the relationship between subsidized fertilizer and nutritional outcomes on farms and concluded that subsidized fertilizer significantly contributed to Malian rural women's diet quality, but that the magnitudes of these effects were small. Assima et al. (2019) decomposed diet diversity by food source (on-farm production, gifts, purchase). The analysis revealed no effects on dietary diversity from the consumption of own (on-farm) production in either the Delta or the Plateau. They found that the effect of subsidized fertilizer on the dietary diversity sourced from purchased food was strong and positive in the Delta du Niger, but negative in the Plateau de Koutiala—concluding that income is the main pathway linking subsidized fertilizers program to women's nutrition outcomes.

Impacts on dietary intake are "second-round" or indirect effects of subsidies. In this paper, we assess "first-round" impacts or direct effects on total fertilizer applied, yields, and crop sales. There are well-known statistical limitations inherent in measuring impacts with single-period, cross-sectional data. With data of this type, we measure the difference between program beneficiaries and non-beneficiaries after the subsidy is distributed, assuming that the two groups are identical except for the subsidy and equally likely to receive it. Yet we know that there is potential for either program or self-selection bias. The bias results from systematic differences in pre-existing farmer characteristics that explain why some in the same areas benefited while others did not (Glennerster and Takavarasha 2013).

Multivariate regression of outcome indicators in order to control for observable variables that do not change with the subsidy is one way we can handle this limitation. We expect these to be related to various endowments that differentiate household status, some of which are measurable. But pre-existing differences may be unobservable or even unimagined—and these might also affect our estimated effects on outcome indicators.

To improve the reliability of our results in this analysis, we compare regression results across several econometric models that aim to control for selection bias and underlying differences between subsidy beneficiaries and non-beneficiaries in different ways. In this respect, we take our example from Mason et al. (2016), who compared estimates of the effects of Kenya's input subsidy program on household maize production, revenues, net income and poverty status among quasi-experimental approaches. Since the authors were able to utilize panel data, they applied various fixed effects and difference-in-difference techniques. Instead, we apply a form of fixed effects (FE) model (Udry 1996; Smale et al. 2019) that controls for idiosyncratic household effects, and several propensity score matching models.

Gollin et al. (2018) caution that to establish clear counterfactual scenarios for assessing poverty impacts, the design of effective research requires forward planning of detailed data collection over a lengthy period of time—before the intervention. In our study, which is based on a single year of data, we focus on immediate, direct effects of the subsidy on fertilizer use, yields, and crop sales in the season of the subsidy receipt.

This study contributes in two ways to a large literature on the impacts of fertilizer subsidies on smallholder farms in Sub-Saharan Africa. First, the analysis addresses a void in the empirical literature about the effects of these programs in West Africa with the exception of several studies conducted in Ghana and Nigeria. In particular, we have found no published studies aimed at evaluating the impact of programs on smallholder farms in Francophone West Africa, including the Sudano-Sahelian region. Not only are the agro-ecological conditions and farming systems quite different, but also how the fertilizer subsidy program is designed and implemented (Smale and Theriault 2019; Thériault et al. 2018). Second, we compare findings across models. As noted by Mason et al. (2016), this provides us on one hand with greater confidence in our results, and on the other, reveals the extent to which results may be sensitive to the model employed.

METHODS

Data

Survey details are provided in Haggblade et al. (2019) and are summarized here. The team selected two of Mali's 14 agroecological zones (the Delta du Niger and the Plateau de Koutiala) as the survey domain because of their importance to agricultural production in Mali and geographical overlap with Feed the Future priority regions (Appendix Figure A1). The sampling frame is composed of all enumeration sections (SE) listed in the most recent General Census of the Population and Housing (Recensement Général de la Population et de l'Habitat, or RGPH 2009).

The survey team stratified all enumeration sections (SE) in each zone by extension system and subsidy form. Subsidy forms include the paper voucher, which has been used from the beginning of the program in 2008, and an e-voucher pilot program, which was introduced in 2016/2017 in the Delta du Niger, extension structures include the highly structured system of the Office du Niger (ON) system and less structured system of the Directions Régionales de l'Agriculture (DRA); in the Plateau de Koutiala, they include the highly structured system offered by the Compagnie Malienne pour le Développement du Textile (CMDT) and the DRA. (See Thériault et al. 2018b for a more detailed discussion of each system).

The sampling took place in two stages. The primary sampling unit was the SE. SEs were randomly selected within each of the eight strata with probability proportional to size of population. The team selected 20 SEs in each of the structured extension systems (ON and CMDT) and 10 SEs in each of the DRA strata, for a total of 60 SEs per agro-ecological zone (AEZ) or 120 in total.

In the second stage, the survey team visited each selected SE in order to compile an exhaustive list of farm households (Exploitations Agricoles Familiales, or EAFs) and selected 20 per SE using simple random sample with a random start from the list. In total, the sample consisted of 2400 farm households, allocated among zones and strata (Figure 1).

Four survey teams implemented the survey in each of the 120 selected SE's. Each team consisted of one supervisor and three numerators, including both women and men. To ensure data quality, a three-member monitoring team visited each team in the field and in between visits maintained daily phone contact with supervisors. This monitoring team included a statistician, a survey expert and an agricultural economist from the ECOFIL (Economie de la Filière) unit of Mali's Institute d'Economie Rurale (IER).

Data collection took place during five rounds of visits over the course of a single cropping season from the end of September 2017 through March of 2019. Survey rounds allowed the team to collect data during all phases of the cropping cycle. Following initial demographic inventories of household members, plot managers, plots and assets, the team recorded land preparation, planting, weeding, harvesting and marketing. Nonfarm income and transfers were reported. Diet diversity was measured pre- and post-harvest. Each round of interviewing began with a two-day pretesting of draft questionnaires in an unsampled village. Based on this experience, the research team revised and finalized questionnaires for full administration in the 120 selected SEs.

Our analytical sample is 9,194 plots allocated to target crops in the 2017/18 cropping season by 2,398 households.[1] In some models, the number of observations is reduced due to missing values in independent variables.

Outcome variables

Outcome variables are defined and summarized by subsidy receipt in Table 1. The fertilizer subsidy is intended to enhance crop yields by augmenting rates of fertilizer use where fertilizer is not used at all or in quantities that are below recommendations. Such is the generally the case on the aged and degraded soils found in much of Mali's agriculture. National average rates of nitrogen and phosphate fertilizer application are only 14 kg per hectare of arable land (Theriault et al. 2018).

Intermediate outcomes include the amount of subsidized fertilizer applied (kg/ha) and the total quantity of fertilizer applied (kg/ha). Target crops in our survey zones include cotton, maize, rice, sorghum and millet. Cotton, fully-controlled, irrigated rice and maize receive 100% of the subsidy for each hectare planted, other rice receives 50%, and sorghum and millet receive 33% per hectare planted in the crop (MA 2019; Kergna, pers. comm. April 20, 2020).

---

[1] Variables were trimmed at the upper first or fifth percentile (depending on the variable) with outliers replaced by median values.

The immediate, direct outcome variable is crop yield. Cotton is entirely a cash crop, but Malian smallholders grow other target crops for subsistence as well as cash. Our second direct outcome variable is target crop income. We measure target crop income as gross revenues from sales of the 2017/18 crop harvest (harvest generally occurs from October to January), as reported by farmers for the period from harvest through July of 2018.

The third outcome variable is the quantity (kgs) of all crops sold, including but not limited to target crops. This variable is reported in quantities because we did not request revenues for all crops. Pathways to this outcome might include a re-allocation among crops as a result of the subsidy on target crops. For example, increasing the productivity of a foodcrop (rice, maize, sorghum, millet) could enable some smallholders to meet their needs on less land and grow an additional cash crop. Another pathway might be leakage of fertilizer destined for the target crop to other fertilizer-responsive crops.

The statistics in Table 1 show that on average, all farmers applied at least some fertilizer to their target crops even when they did not receive the subsidy—with the exception of their cotton plots. Yields were higher on all plots receiving subsidized fertilizer except for cotton plots. On cotton plots, yields appear to be lower on plots receiving subsidized fertilizer but the difference is not statistically significant. Target crop income was higher on rice and maize plots receiving the subsidy, but any differences were not significant between subsidized and non-subsidized plots of millet, sorghum or cotton.

Fixed effects model

Udry's (1996) model restricts attention to plot-level variation in an outcome variable while controlling for crop-household-year fixed effects. The estimation is as is:

$$Y_{icj} = \boldsymbol{X}_{icj}\boldsymbol{\beta} + \boldsymbol{\alpha}_{icj}\boldsymbol{\gamma} + \lambda_{cj} + \boldsymbol{\varepsilon}_{icj}, \qquad (1)$$

where Y_{icj} is an observed outcome variable on plot *i* planted with crop *c* cultivated by a household *j* in the survey year. Udry applied the model to panel data collected in Burkina Faso in order to test for gender differentials. Here we apply the model as a form of fixed effects approach in cross-sectional data, eliminating *j*, as in Smale et al. (2019). Our vector $\boldsymbol{X}$, like Udry's, includes plot characteristics, with coefficients $\boldsymbol{\beta}$. λ_{cj} are crop-household fixed effects. $\boldsymbol{\alpha}$ designates, in our case, whether or not subsidized fertilizer 1) received by paper voucher or 2), both paper voucher and electronic voucher was applied to the plot[2]. If the elements of $\boldsymbol{\gamma}$, the vector of coefficients on the binary variables in $\boldsymbol{\alpha}$, are not statistically different from zero, ceteris paribus, we fail to reject the null hypothesis of the subsidy had an effect on the outcome of interest[3].

The model controls for heterogeneity at the household level brought about by household and market characteristics. For the purposes of this analysis, the main shortcoming of this approach is that we cannot test for crop-specific outcomes because we use crop as a control variable. The

[2] The category includes both paper and electronic vouchers, since among the e-voucher beneficiaries less than 0.15% of them received their subsidized fertilizer exclusively through the e-voucher.
[3] We estimate the model with *xtreg (fe)* and crop-household rather than year effects in STATA, after confirming that the regression results are the same as if we had estimated a linear regression with dummy variables for each crop-household combination. Dummy variables are a special case of fixed effects. We use *xtreg* because such a large number of dummy variables is computationally challenging and results in an inflated measure of fitness (R-squared).

primary benefit is that because we have also controlled for household variation (observed and unobserved), our specification is parsimonious with respect to covariates. We include only plot characteristics in this model, along with the subsidy effect. We can also easily test for a gender-differentiated effect.

Binary propensity score matching (binary)

In the context of a randomized experiment, the average treatment effect (ATE) is estimated as

$$ATE = E(Y_1\text{-}Y_0) \qquad (2)$$

where Y_1 and Y_0 is the outcome variable of interest with and without treatment. However, the fertilizer subsidy program is not randomly assigned. The impact evaluation of fertilizer subsidies is therefore challenging due to the traditional problem of selection bias in non-experimental design studies. We attempt to address this problem by using propensity score matching methods to generate treatment and control groups based on vector of plot and household characteristics. Since all farming households in Mali are in principle eligible for the fertilizer subsidy, and we are in some models estimating marginal effects on those who received the subsidy, we are interested in the average treatment effect on the treated (ATT) (Theriault et al. 2018); Liverpool-Tasie 2014).

Propensity score matching (PSM) consists of three sequential steps. First, a dummy variable w is assigned to each plot that assumes a value of 1 if the plot is treated and 0 otherwise. In this study the treatment dummy variable represents application of subsidized fertilizer at plot level. Secondly, we estimate a logit regression model of the type

$$\pi_{ic} = \underline{\boldsymbol{X}}_{ic}\underline{\boldsymbol{\beta}} + \boldsymbol{u}_{ic}. \qquad (3).$$

The vector of coefficients $\underline{\boldsymbol{\beta}}$ corresponds to the vector $\underline{\boldsymbol{X}}$. Each coefficient β indicates the contribution of the corresponding covariate X to predicting inclusion of units in the treatment group. To control for heterogeneity in this model, we add a set of variables that measure the characteristics of the plot manager and household, including: number of male and female adults in the EAF, total area of land owned by the EAF, plot size measured by GPS[4],revenues from off-farm work, age and status of the plot manager, and number of years that the plot manager has been a member of his or her most important farmers' organization (Table 2).

Third, the propensity scores variable is generated as

$$pscore = prob(w = 1/X) = \psi(\pi) \qquad (4)$$

Matching plots based on propensity scores has the advantage of eliminating biases due to observable plot and household characteristics (Rosenbaum and Rubin, 1983). Two assumptions underpin the validity of the matching method. The first is conditional independence assumption (CIA), which means that after controlling for observed plot and household characteristics, the potential outcomes are independent of assignment to treatment (w). Formally, this assumption is expressed by the formula

$$(Y_0, Y_1) \perp w | X \qquad (5)$$

---

[4] Trimmed at 1% with outliers replaced by the median.

The second assumption is the overlap condition, which ensures that plots with the same observed characteristics have a non-negligible probability of being in the treated or control group.

$$0 < pscore < 1 \qquad (6)$$

More precisely, we check the overlap condition through a visual analysis by plotting the graphs of the density distribution of the propensity score (*pscore*) of the two groups of treatment. Under these underly assumptions, the average treatment effects on treated (ATT) is determined by

$$ATT = E(E(Y_1|w = 1, X) - E(Y_0|w = 0, X)|w = 1) \qquad (7)$$

The conditional independence assumption (CIA) implies that conditional on the propensity score, the distribution of observed characteristics of plots and households is the same, that is to say balanced, for the treated and untreated units. Therefore, to assess the quality of the matching, it is necessary to verify that the distribution of the variables is balanced between the treated and untreated groups.

Based on the suggestions of Rosenbaum and Rubin (1983), we use both a standardized bias and a t-test to test the statistical difference in the distribution of the propensity scores of the covariates to ensure that the balancing property is satisfied. The t-statistic for the covariate-balancing test is less appropriate because it depends on the variance and the sample size of each group. The literature recommends the standardized bias test to assess the balancing of the covariates before and after matching because it allows comparisons on the same scale. An absolute value of the standardized bias less than 10% generally indicates the balance of the covariates.

Despite meeting the balancing property and overlap condition, PSM estimates may be biased due to unobserved characteristics. Thus, we compute the Rosenbaum (2002) bounds sensitivity analysis to check the robustness of our treatment effects results to hidden bias. It should be noted that although the Rosenbaum bounds sensitivity analysis measures the extent to which unobserved characteristics could alter the PSM estimates, it does not indicate whether these unobservables are in fact present or if they bias our results. Nevertheless, the sensitivity analysis allows us to identify the critical points of unobserved characteristics influence that might challenge the PSM estimates.

Generalized propensity score matching (GPSM)

The foremost advantage of generalized propensity score matching (GPSM) is that we can estimate a marginal treatment effect rather than a simple binary effect. In the case of a continuous treatment such as the amount of subsidized fertilizer received, a dose-response function can provide additional information about inflection points or changes in the size of marginal effects on outcomes as treatment intensifies.

In applying GPSM, we assume that the amount of subsidized fertilizer (kgs) applied to a plot is independent of the potential outcome means conditional on plot and household characteristics. Summary statistics show that there are many plots that did not receive subsidized fertilizer (zero treatment level (w=0)) and that the treatment variable (kilograms of subsidized fertilizer per hectare (w=1)) is not normally distributed. For that reason, we apply the approach developed by Cerulli (2015), which is an extension of the regression adjustment treatment model developed by Wooldridge (2010) for a continuous treatment setting. Cerulli's approach does not require the full normality assumption and takes into account the fact that many units may have zero treatment level.

Following that approach, we define the potential outcome model with continuous treatment as follows:

$$\begin{cases} \boldsymbol{Y}_1 = \alpha_1 + \underline{\boldsymbol{X\delta_1}} + h(t) + \boldsymbol{\nu}_1\ if\ w = 1 \\ \boldsymbol{Y}_0 = \alpha_0 + \underline{\boldsymbol{X\delta_0}} + \boldsymbol{\nu}_0\ \ if\ w = 0 \end{cases} \quad (8)$$

Where *w* is the binary treatment variable taking value 1 if subsidized fertilizer is applied to the plot and zero otherwise and *t* is the continuous treatment (dose) ranging from zero to hundreds. *Y* denotes an outcome variable and the vector $\underline{\boldsymbol{X}}$ represents the same confounding variables as in binary approach. $\underline{\boldsymbol{\delta_1}}$ is a vector of coefficients with the marginal response of the treated units to the vector of the covariates $\underline{\boldsymbol{X}}$. $\underline{\boldsymbol{\delta_0}}$ is the vector coefficients of the marginal response of the untreated units to the vector of the covariates $\underline{\boldsymbol{X}}$. $\alpha_0\ and\ \alpha_1$ are constants. $\boldsymbol{\nu}_0\ and\ \boldsymbol{\nu}_1$ are independent and identically distributed error terms. Our interest in this model is *h(t)*, which is a function of the treatment level.

The average treatment effect (ATE) is equal to the dose-response and is calculated as

$$ATE(\boldsymbol{X}, t) = E(\boldsymbol{Y_1} - \boldsymbol{Y_0} |\ \boldsymbol{X}, t) \quad . \quad (9)$$

And the average treatment effects on treated ATT is given by

$$ATT(\boldsymbol{X}, t > 0) = E(\boldsymbol{Y_1} - \boldsymbol{Y_0} |\ \boldsymbol{X}, t > 0)\ . \quad (10)$$

For more details, see Cerulli (2015).

As in the binary PSM method, it is assumed that, subject to the observed covariates, the intensity of the treatment received is independent of the potential outcomes. Therefore, the consistency of the GPSM estimates relies on the balancing property and the overlap condition. To test these fundamental assumptions, we grouped the sample into three blocks according to the distribution of the treatment intensity, cutting at the 25th and 75th percentiles of the distribution.

Similar to the binary approach, we assess the quality of the common support condition through visual inspection by plotting the distribution of the GPSM for the three blocks. To assess the quality of the balancing property, we compute the student t-statistics for the differences in means of each block compared to the other two blocks before matching on GPSM and the equivalent t-statistics after matching on GPSM (Hirano and Imbens, 2004). The standardized variance test computed in the binary case cannot be directly applied in the GPSM model.

RESULTS

Descriptive findings

Fertilizer applied to plots of target crops

Summary statistics for the amount of subsidized fertilizer applied by plot managers to target crops, total fertilizer applied, and the share of subsidized fertilizer are shown in Table 3, by type of plot manager. Amounts applied per ha to target crops are about 10% higher on average for plots managed by the Chef (head of household) than for those managed by the Chef des travaux (designated head of works), and more than twice as high as those managed by other household members. All but 1% of Chefs, and 8% of Chef des travaux are male. By contrast, nearly 4 in 5 (79%) of other members who manage plots are female. Plots managed by other members represent only about 5% of all plots planted to target crops; subsidized fertilizer also represents on average 84% and 81% of all fertilizer applied to the target crop plots managed by the Chef and Chef des travaux, but only 53% of that applied by other household members to plots they manage.

Differences by target crop are also meaningful (Table 4). The mean amounts of subsidized fertilizer applied to millet and sorghum are only about 8 kg/ha, as compared to 161 for rice, 154 for maize and 178 for cotton. Recommendations are: for fully irrigated rice, 100 kg DAP and 200 kg urea; for submerged rice, 50 kg DAP and 100 kg urea; for maize, 100 kg of *complexe céréale* and 150 kg urea; and for millet and sorghum, 100 kg of *complexe céréale*. While 200 kg of *complexe coton* and 50 kg of urea are recommended for cotton, extension agents often state that 150 is a good rate of use for *complexe coton* (Alpha Kergna, Pers. Comm. April 2020). Although the recommended type for the crop was most often used by farmers, they also used, or reported they used, other combinations of types. The results do suggest that at the mean, even with the subsidy, total kgs applied per ha are below the recommended amounts for all crops. Without the subsidy, of course, use rates are dismal.

The share of subsidized fertilizer in total fertilizer applied rises from about two-thirds for millet, to 72% for sorghum, more than three-quarters (76%) for rice, 92% and 98% for maize and cotton, respectively.

Regression models

Fixed effects model

Results of the fixed-effect regression are shown in Table 4. Considering all crops combined, estimated effects of the subsidy received via paper voucher on fertilizer use rates, yield, quantities of all crops sold and target crop revenues are highly significant. The additional effect of receiving fertilizer through the evoucher pilot program does not influence any of the outcomes significantly except for target crops sold, where it is weakly significant. Among control variables, larger plot size reduces per ha application rates and yields—which is consistent with expected patterns reported in the literature that the more extensive the area, the lower the intensity of input use because of labor constraints. Plot age is positively associated with higher rates of fertilizer use because farmers seek to compensate for declining soil fertility, but also with better yields and more crop sales. Older plots are likely to be collectively managed. Rainfed plots receive less fertilizer than irrigated plots and also generate lower yields when we control for fixed effects of crop-household. Rice is the target crop for which most plots are irrigated but some are not. Neither soils nor relief effects are jointly significant and these are not reported in Table 4. Soil types and topography are likely to be highly correlated with the crop (Smale et al. 2019).

Another finding—not presented here to conserve space—is that when we estimate the same models for cereals only (maize, sorghum, millet, rice) and exclude cotton, the significance and direction of effect remains the same. The magnitudes of the effects of the subsidy on yields is smaller by 10 kg per ha, but effects on total fertilizer use per ha and quantity of crops sold change by less than a kg. We also observe a slight offsetting effect of manure use on fertilizer application rates on plots planted to cereals that disappears when we account for cotton. Alia (2017) also found a substitute relationship between fertilizer and manure for cereal crops in Burkina Faso. Recall that it is not feasible to estimate regressions per crop while also controlling for crop-household fixed effects.

We also ran the models with an additional variable for sex of plot manager. When we control for subsidy receipt, this variable is not statistically significant in the fertilizer use or yield equations, but is highly significant in quantity of all crops sold and target crop revenues. Effects of the subsidy are less significant. We surmise that this result reflects the strong correlation between sex of plot manager and subsidy benefits.

Binary PSM model

We begin with model diagnostics**.** After matching, the value of the standardized bias, for all of our covariates excepts for intercrop, lies between -10 and 10, which indicates that the matching has reduced the overall balancing bias (Figure 2). The absolute value of the standardized bias is slightly greater than 10 for intercrop variables but remains close to 10. This result indicates that we have achieved an acceptable balancing distribution of our covariates after matching. Balance checks comparing means of all explanatory variables before and after matching are provided in Appendix Table A1.

Figure 3 shows the density distributions of propensity scores for the two treatment groups in unmatched and matched samples. The probability of being in the treated group or the control group for the treated and untreated units is greater than zero and less than one. Some units, representing 6% of the sample, fall outside this range. We trimmed these observations to ensure a correct match and meet the common support condition (equation 6).

Table 5 presents the PSM estimates of the treatment effects of subsidized fertilizer on the outcome variables. The table presents both the results of the full sample and the results of the separate regressions for target crops. The results show that overall, the quantity of fertilizer applied, the crop yield, the quantity of crop sales and the income from target crops sales are positively and significantly associated with the use of subsidized fertilizer by the plot manager.

However, examining the results of separate regressions reveals differences in subsidized fertilizer effects across crops. Though the quantity of fertilizer applied is positively associated with subsidized fertilizer in all regressions, the results for the other three outcomes vary by crop. While subsidized fertilizer results in positive, significant effects on yield for rice, millet and maize plots, it has no significant effect on outcomes for cotton plots. Separate regression for rice indicates that the quantity of crop sales and the income of target crops increase with receipt of subsidized fertilizer. Quantities of all crops sold appears to rise significantly for sorghum, but sorghum sales do not. Millet sales appear to rise with subsidy receipt.

Tables A2-7 in the appendix present the p-value of the upper bound significance levels for a range of critical values of gamma (Γ), which characterizes the influence of the unobserved covariates through our outcomes variables. The value of Γ for which the level of significance of the upper bound is greater than 0.1 is the critical value for which unobserved covariates would undermine the estimated average treatment effects on treated. If the lowest Γ value for which the p value is greater than 0.1 is close to 1, then the estimated average treatment effect is sensitive to the presence of a hidden bias due to unobserved covariates. Conversely, if the value of Γ for which the p value is greater than 0.1 is around 2, then the estimated average treatment effect is rather robust to the presence of unobservable.

Results of the Rosenbaum-bounds test statistics for both the full sample regression and separate regressions are shown in Tables A2-7 across all of our outcome variables. For the full sample regression, the Γ value at which the p-values for the upper bound significance level is below 0.1. The corresponding value is 1.2 for income from target crop sales and 1.6 for yield. These results indicate that unobserved characteristics would have to increase the odds ratio by at least 20% in order to undermine the inference about the ATT estimates for target crop income and by 60% for yield. For the quantity of all crop sales and fertilizer applied, the Γ value exceeds 2, suggesting robustness of these two variables to hidden bias.

Tests therefore demonstrate that the robustness of results to hidden bias due to unobserved characteristics varies across the outcomes variables. Overall, our estimates are robust to the influence of unobserved characteristics. Sensitivity analysis in the separate regressions for millet shows that the hidden bias compromises our inferences of treatment effects regarding the income from sales of target crops. That is to say, income is sensitive to unobserved characteristics. The same is true of the separate regressions for maize and cotton. Sensitivity analysis of the separate regressions for rice shows that our inferences of treatment effects are robust for all outcome variables.

Generalized propensity score matching

The results of balancing tests for the GPSM model are reported in Table 6. A quick perusal of the blocks indicates that in block 1, treatment intensity ranges between 0 and 152 kg/ha while in block 2, it ranges from 153 to 230 kg/ha and in block 3, it lies between 231 to 326 kg/ha. Before matching on GPSM, the t-statistics of almost all observed covariates exceeds 1.96, indicating unbalanced distribution of these observed variables. After matching on GPSM, the t-statistics of the vast majority of observed covariates falls below 1.96, which is the critical value of the t-statistics with a p-value at 0.05 (those that are outside the range are in bold). Statistical results indicate that we have achieved the balancing property for most of the observed covariates.

As shown in Figure 4, the distribution of the generalized propensity score is strictly between zero and one for all the blocks. Figure 4 also shows the overlap in the distribution of the generalized propensity score between the blocks. Our sample generally satisfies the overlap condition.

The dose-response functions graphed in Figure 5 show the relationships between subsidized fertilizer applied (kg/ha) and the predicted outcome variables of yield (kg/ha) and crop sales (FCFA, kg/ha) considering all targeted crops. The figure depicts a positive marginal effect of subsidized fertilizer on all outcomes of interest, but underscores a new point that is not apparent in the other models: the marginal effect (per kg) of subsidized fertilizer on the outcome variables changes over the predicted range in the amount of subsidized fertilizer applied. To illustrate this point, inflection points were computed by taking derivative of the dose-response function, which is equal to the derivative of h(t), and setting it to zero.

With respect to yield, the expected response of yield (kg/ha) to an increase of subsidized fertilizer (kg/ha) begins to increase after an inflection point at 98, and continues increasing through the whole range of treatment levels. This means that an intensity of subsidized fertilizer less than 98 kg/ha hectare does not have a significant effect on yields and is relatively constant at low levels of subsidy. However, intensities of subsidized fertilizer above 98 kg/ha translate into steeper yield response, meaning that the minimum treatment necessary to have a positive impact on yield is 98 kg/ha (roughly 2 sacks of 50kg).

For income from sales of targeted crops, the dose-response curve is convex, declining at first to a minimum of zero at 97 kgs/ha of subsidized fertilizer. Thereafter, sales income increases to reach a value of 900 thousand when the highest amounts of subsidized fertilizer are applied. The shape of this curve may reflect that at smaller treatment levels, changes in crop production are largely consumed (in the case of sorghum and millet, in particular, since these receive small amounts of fertilizer, are less fertilizer-responsive, and are staple cereals) rather than sold.

With regard to the quantity of all crops sold, the dose-response curve is flat from the start to around 195 kg/ha of subsidized fertilizer, suggesting a weak response for lesser amounts. After that point, the dose-response curve shows rapid growth, which indicates a greater marginal effect. This suggests that to affect crop sales substantially, subsidized fertilizers must reach at least 195 kgs/ha.

Considering all target crops provides a general picture that confirms largely positive, but varying marginal effects of the fertilizer subsidy on the yield and income from target crops, as well as crop sales of all crops. To understand differences among crops, we also conducted separate dose-response regressions using the same outcomes for each target crop except for sorghum. We did not measure sorghum yields given the extent of earlier work we conducted on sorghum (see, for example, Haider et al. 2018), and the lack of significance found with respect to outcome variables when we used binary PSM on sorghum plots (Table 6). Similarly, the results we report above suggest little significant effect on millet production or outcome variables. Below, we report results for rice, maize and cotton.

The dose response function for rice yields presents a convex shape for low amounts of the subsidy and concave shape for high treatment levels (Figure 6). After 65 kg/ha of subsidized fertilizer, the marginal yield response is positive and rising at an increasing rate until a maximum of 283, which is near the recommended rate of fertilizer application (though the result depends on the type of fertilizer applied). Regarding the income from sales of target crops, the dose response function shows the same pattern as for yield but is less marked. The dose-response indicates that quantity of all crops sold also begins to respond to an increase in subsidized fertilizers at 65 kg/ha and continues to increase over the entire remaining range, reaching a value of 10,000 kg at the highest about of subsidized fertilizer received per ha reported in the sample. These results suggest, but in no way prove, that subsidized fertilizer received for rice may have been allocated to other crops.

The dose-response function for maize (Figure 7) shows a positive predicted yield response to subsidized fertilizer above 87 kg/ha through 265 kg/ha. The total recommended rate in kgs for maize is 250 kg/ha. Afterwards, marginal effects on maize yields per kg of subsidized fertilizer decline. Regarding the target crop income, the dose-response curve shows a flattened parabolic shape with a minimum at around 120 kg/ha of subsidized fertilizer. The marginal effect of subsidized fertilizer on the income of target crops slowly decreases at low treatment levels, below 120 kg/ha and similarly increases slowly at high treatment levels. Overall, income from target crops sales responds weakly to subsidized fertilizer perhaps because maize is a subsistence food crop for most of cotton-grower households. This is consistent with Smale et al. (Forthcoming) who estimated the share of maize in the Malian household budget to be small at around 2-4% in either rural or urban areas. For the quantity of crop sales, the dose response function shows a continuously positive and slow progression over the right side of the subsidy range. That is to say, subsidized fertilizer amounts of up to 145 kg/ha have no effect on the quantity of sales of all crops and it is only after that amount that the effects of the subsidy become significant. Again, these results imply spillovers to other crops at higher levels of treatment.

Figure 8 depicts the relationships of subsidized fertilizer and the main outcome variables for cotton. The dose response for yield show a distinct U-shaped relationship between subsidized fertilizer and cotton crop yield. This suggests that positive yield response per kg of subsidized fertilizer received is observable only at higher rates of subsidized (and likely, total) fertilizer use. For income from target crop sales, the dose response function is flat indicating there is no effect of subsidized fertilizer on income gain from the sales of cotton. With regard to the quantity of crop sales, the dose response function actually declines as the level of treatment increases, thus the subsidized fertilizer results in a decrease in the quantity of other crops sold.

CONCLUSIONS

In this paper, we tested the direct effects of subsidized fertilizer received by farmers and applied on plots of target crops (sorghum, millet, maize, rice, sorghum). The intermediate outcome variable was total fertilizer applied per hectare, and outcome variables were yield, target crop income, and quantities sold of all crops.

Descriptive findings suggest that at the mean, fertilizer use rates were below the recommended amounts on all target crops, and especially on millet and sorghum. This should be confirmed in further analysis by converting all fertilizer quantities to nitrogen nutrient kgs, which standardizes across types.

All farmers applied at least some fertilizer to their target crops even when they did not receive the subsidy—with the exception of their cotton plots. The average share of subsidized fertilizer in total fertilizer applied rises from about two-thirds for millet, to 72% for sorghum, more than three-quarters (76%) for rice, 92% and 98% for maize and cotton, respectively. Mean yields were higher on all plots of target crops receiving subsidized fertilizer except for cotton plots. Target crop income was higher for rice and maize receiving the subsidy but not for cotton, sorghum, or millet.

The results of fixed effects, binary PSM, and GPSM analyses showed strongly that overall, the fertilizer subsidy had a positive effect on total fertilizer applied per ha, yields per ha, and crop revenues of target crop, but also on quantities of all crops sold. The FE model cannot differentiate by crop, however. The binary PSM showed us only average effects, and the GPSM showed us how the marginal effect of the subsidy varies over levels of the subsidy in a continuous treatment framework.

PSM findings underscored differences among crops. Subsidy effects on millet and sorghum outcome variable were weak or not statistically significant, but strong for rice. If, for rice and maize, the subsidy made it possible to improve yields, for cotton, the subsidy only allowed an increase in the quantities of fertilizers used without improving productivity. This result was confirmed by follow-up feedback discussions with farmers surveyed, who attributed this poor yield response to poor cotton seed quality (Sissoko et al. 2020).

By estimating the dose-response functions, we were able to identify efficiency intervals in which the fertilizer subsidy had the positive effect on fertilizer use, productivity and crop sales—although these varied from one crop to another. There was no positive marginal effect of subsidized fertilizer below 65 kg/ha for rice and 87 kg/ha for maize. The graphs also show peaks at high levels of subsidized fertilizer for both crops that are likely to correspond to total fertilizer use that is above recommended levels, with declining marginal returns after that point. For rice, marginal effects on rice revenues and quantities of all crops sold remained strong. This last result was observable also for maize, suggesting some spillovers to non-target crops. No positive effect on cotton yields, cotton revenues or quantities of all crops sold was discernible regardless the level of treatment.

POLICY IMPLICATIONS

Key findings with important policy implications emerge from this work. First, even in the presence of the subsidy, farmers applied less than the recommended rates per ha on all target crops—and especially to sorghum and millet. Additional work is needed to verify this finding after converting units to nitrogen nutrient kgs, which standardizes across fertilizer types. Agronomic optima are distinct from economic optima, and there may be reasons why farmers reallocate fertilizers from one crop to another. Divergence from optima also highlight highlights the importance of adopting sustainable agricultural practices to improve soil fertility.

Second, while individual farmers are eligible, the fertilizer subsidy program is clearly transmitted primarily through the male Chef (head of household) and Chef des travaux (designated head of work). The extent to which it directly benefits other plot managers who are household members likely depends on a intrahousehold process of negotiation. The unintended effect of the subsidy may be to exacerbate rather than reduce youth and gender inequalities. There is a need to revisit the program design and implementation to ensure its inclusivity. Improving access to inputs, such as fertilizer, to women and young men can increase their influence on other decisions, which may lead to greater equity within the household and enhance efficiency in production (Haider and al. 2018).

Third, strong effects of the fertilizer subsidy when all crops are combined appears at first glance to be a positive finding. However, differences among crops point to some possible shortcomings of program design. Is it crops, farming systems, or farmer types that should be targeted, if targets are pursued?

For example, all of our statistical results point to a deadweight fiscal loss for the fertilizer subsidy on cotton. That is, subsidized fertilizer represented an average of 97% of the total fertilizer farmers applied to cotton plots, but no yield or target income effects are detectable on average or across the full range observed in the data. Though a factor we have not been able to measure in our analysis, such as seed quality, may explain this result, it does raise questions concerning program design.

Lack of effect on sorghum and millet outcomes also suggests some incongruity in subsidy design. On one hand, sorghum and millet are often shown to be less responsive to fertilizer than irrigated rice or maize when grown in an environment with sufficient moisture, justifying less subsidization. On the other, it may be that the amounts used on these crops simply remain too low to pick up a positive yield response.

Strong effects are seen across all outcome variables for rice, but particularly within a particular range of subsidized fertilizer applied. This warrants further investigation. Subsidy effects on maize yields are strong, but not on other outcomes. We deduce that much of this maize is in fact consumed on farm, rather than sold. Given that this finding is confirmed in other studies, is it the desired effect of the subsidy?

REFERENCES

Alia, Didier Y. 2017.Agricultural input intensification, productivity growth, and the transformation of African agriculture. Theses and Dissertations--Agricultural Economics. 59. https://uknowledge.uky.edu/agecon_etds/59

Assima, A., Zanello, G., and Smale, M. 2019. Effects of fertilizer subsidies on women's diet: quality by food supply source in Mali. Feed the Future Innovation Lab for Food Security Policy, Research Paper 152.

Cerulli, G. 2015. Ctreatreg: Command for fitting dose–response models under exogenous and endogenous treatment. *Stata Journal*. doi: 10.1177/1536867x1501500405.

Druilhe,Z. and J. Barreiro-Hurlé. 2012. Fertilizer Subsidies in Sub-Saharan Africa. ESA Working Paper No. 12-04. Food and Agriculture Organization of the United Nations. Rome, Italy.

Glennerster, R and K. Tajavarasha 2013. Running Randomized Experiments: A Practical Guide. Princeton University Press 2013.

Gollin, D., Probst, L. T., & Brower, E. 2018. *Assessing Poverty Impacts of Agricultural Research: Methods and Challenges for CGIAR*. Rome: Independent Science and Partnership Council (ISPC).

Haggblade, S., M. Smale, A. Assima, N. Keita, A. Kergna, Y. Kone, V. Theriault and A. Traore. 2019. Overview and Results of a Farm Household Survey in two agro-ecological zones of Mali, 2017/18. FSP Research Paper 140. East Lansing. Michigan State University.

Haider, H., M. Smale, and V. Theriault. 2018. Yield Response of Dryland Cereals to Fertilizer in Mali: Insights from Household Surveys. Research Paper 92. Feed the Future Innovation Lab for Food Security Policy, Mali.

Haider, H., M. Smale, and V. Theriault. 2018.Intensification and intrahousehold decisions: Fertilizer adoption in Burkina Faso. *World Development*, 105:310-320.

Hirano, K. and Imbens, G. W. 2004. "The Propensity Score with Continuous Treatments," Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives: An Essential Journey with Donald Rubin's Statistical Family, (2001), pp. 73–84. doi: 10.1002/0470090456.ch7.

Holden, S. T. 2019. Economics of farm input subsidies in Africa. *Annual Review of Resource Economics* 11:501–22.

Jayne, T., Mason, N., Burke, W.,J., and Ariga, J. 2018. Taking Stock of Africa's Second-Generation Agricultural Input Subsidy Programs. *Food Policy*, 75: 1-14.

Kato, T. and Greeley, M. 2016. Agricultural Input Subsidies in Sub-Saharan Africa, In: Development Studies – Past, Present and Future, IDS Bulletin 47: 33-48.

Kone, Y., A. Kergna, A. Traore, N.Keita, V. Theriault, M. Smale, S. Haggblade. 2019a. Regard sur les origines de la subvention des engrais au Mali. FSP Bulletin Politique 95. East Lansing, Michigan State University.

Koné, Y., A. Kergna, A. Traoré, N. Keita, S. Haggblade, V. Thériault et M. Smale. 2019b. Constats empiriques sur le programme pilote de subvention e-voucher au Mali. FSP Bulletin Politique 93. East Lansing, Michigan State University.

Liverpool-Tasie, S. O. 2014. Do Vouchers Improve Government Fertilizer Distribution? Evidence from Nigeria. Agricultural Economics 45: 393–407.

Mason, N.M., Wineman, A., Kirimi, L., Mather, D. 2016. The Effects of Kenya's 'Smarter' Input Subsidy Programme on Smallholder Behaviour and Incomes: Do Different Quasi-experimental Approaches Lead to the Same Conclusions? *Journal of Agricultural Economic*s, Vol. 68, No. 1, 2017, 45–69 doi: 10.1111/1477-9552.12159.

Ministère d'Agriculture (MA), Mali, 2019. Manuel de procédures de gestion Administrative, Financière et comptable de la subvention des intrants Agricoles. Bamako, Mali.

Morris M., Kelly V. A., Kopicki R. J., Byerlee D. 2007. Fertilizer Use in African Agriculture: Lessons Learned and Good Practice Guidelines. Washington, DC: World Bank.

Rosenbaum, P. R. and Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1083), pp. 170–184. doi: 10.1017/CBO9780511810725.016.

Rosenbaum, P. R. 2002. Covariance adjustment in randomized experiments and observational studies. *Statistical Science*, 17(3), pp. 286–327. doi: 10.1214/ss/1042727942.

Sissoko, M., Assima, A., Keita, N. and Koné, Y. (2020) Restitution de l'enquête IER/MSU/2017-18 auprès des ménages agricoles sur l'utilisation des intrants dans la zone du plateau de Koutiala. Feed the Future Innovation Lab for Food Security Policy

Smale, M., L. Diakité, and N. Keita. 2011. Location, vocation, and price shocks: cotton, rice and sorghum farmers in Mali. *Development in Practice* 21 (4-5): 590-603.

Smale, M., Theriault, V., Haider, H., Kergna. A. 2019. Intrahousehold Productivity Differentials and Land Quality in the Sudan Savanna of Mali. Land Economics. 95(1): 54-70.

Smale, M. and Theriault, V. 2019. A Cross-Country Synopsis of Fertilizer Subsidy Programs in Sub-Saharan Africa. Feed the Future Innovation Lab for Food Security Policy, Research Paper 124, Michigan State University, East Lansing.

Smale, M., Theriault, V., and Vroegindewey, R. Forthcoming. Nutrition Implications of Dietary Patterns in Mali. African Journal of Agricultural and Resource Economics.

Thériault, V., M. Smale, Y. Kone, and S. Miller. 2018a. Rationalizing Investments in Mali's Agriculture Sector: Simulating Growth Options to Inform Strategic Investment. Technical Report, Alliance for a Green Revolution in Africa (AGRA). East Lansing, Michigan State University.

Thériault, V., Smale, M., and Assima, A. 2018b. The Malian fertiliser value chain post-subsidy: an analysis of its structure and performance, Development in Practice 28 (2), 242-256.

Udry, Chris. 1996. Gender, Agricultural Production, and the Theory of the Household. Journal of Political Economy 104 (5): 1010-1046.

Wanzala-Mlobela, M., Fuentes, P., and Mkumbwa, S. 2013. Practices and policy options for the improved design and implementation of fertilizer subsidy programs in sub-Saharan Africa. NEPAD Agency Policy Study, A joint publication by the NEPAD Planning and Coordinating Agency (NPCA), the United Nations Food and Agriculture Organization, and the International Fertiliser and Development Centre (IFDC).

Table 1. Summary statistics for intermediate and outcome variables by subsidy receipt

Outcome variables		Subsidy	No subsidy
Intermediate		mean	
Subsidized fertilizer applied (kg/ha)			
	Millet***	7.62	0.00
	Sorghum***	7.81	0.00
	Rice***	161	0.00
	Maize***	154	0.00
	Cotton***	178	0.00
Total fertilizer applied (kg/ha)			
	Millet***	43	6.42
	Sorghum***	39	4.50
	Rice***	241	125
	Maize***	187	50.1
	Cotton***	183	0.00
Outcomes			
Yield (kg/ha)			
	Millet***	594	467
	Rice***	2920	1786
	Maize**	1593	1373
	Cotton	930	1047
Target crop income (FCFA)			
	Millet	34563	33481
	Sorghum	9328	7798
	Rice***	943007	351883
	Maize***	37567	13957
	Cotton	506558	358646
All crop sales (kgs)***		6222	2965

n=9194 plots. *** p <.01, **p<.05

Source : Authors, based on PRePoSAm survey.

Table 2. Type and definition of independent variables

Variable	Type	Definition
CT	dummy	Farmer received paper voucher
EV-CT	dummy	Farmer received both paper voucher and evoucher
Intercrop	dummy	intercropping on the plot
Plot size	Quantitative (ha)	Plot size measured with GPS
Plot age	Quantitative (yrs)	Plot age
Soil*	dummies	Soil type (loamy, clay,
Relief*	dummies	Plot relief
Nonfarm income	Quantitative (FCFA)	Revenues from off-farm work
Manure	dummy	Manure used/not used on the plot
Adult males	Quantitative	Number of male adults in the EAF
Adult females	Quantitative	Number of female adults in the EAF
Membership	Quantitative (yrs)	Plot manager past membership in a farmers' organization
Farm area	Quantitative (ha)	Total area of land farmed by the EAF
Manager age	Quantitative (yrs)	Age of the plot manager
Manager	dummies	Status of the plot manager in the EAF (chef, designate, other family member

Source : Authors, based on PRePoSAm survey

Table 3. Total and subsidized fertilizer applied to plots of target crops, by plot manager status

Variable	mean	sd	min	max
Total subsidized fertilizer applied (kg/ha)				
Chef EAF (Head of household)	111	109	0	326
Chef des travaux (Head of works)	100	109	0	327
Other member	31.3	76.6	0	326
All plots of target crops	103	109	0	327
Total fertilizer applied (kg/ha)				
Chef EAF(Head of household)	130	113	0	361
Chef des travaux(Head of works)	120	113	0	357
Other member	52.3	93.1	0	357
All plots of target crops	123	113	0	361
Ratio of subsidized fertilizer to total fertilizer applied				
Chef EAF(Head of household)	0.847	0.333	0	1
Chef des travaux(Head of works)	0.805	0.373	0	1
Other member	0.533	0.491	0	1
All plots of target crops	0.825	0.356	0	1

. Source : Authors, based on PRePoSAm survey

Table 4. Total and subsidized fertilizer applied to plots of target crops, by crop

Total subsidized fertilizer applied (kg/ha)				
	mean	sd	min	max
Millet	7.62	17.9	0	75
Sorghum	7.81	18.3	0	74.7
Riz	161	120	0	327
Maize	154	82	0	292
Cotton	178	60	0	279
All plots of target crops	103	109	0	327
Total fertilizer applied (kg/ha)				
	mean	sd	min	max
Millet	16.7	28.7	0	100
Sorghum	13.9	26.7	0	107
Riz	209	109	0	361
Maize	167	79	0	301
Cotton	180	57	0	282
All plots of target crops	123	113	0	361
Subsidized fertilizer share of total (kg/ha)				
	mean	sd	min	max
Millet	0.633	0.473	0	1
Sorghum	0.725	0.440	0	1
Riz	0.761	0.392	0	1
Maize	0.918	0.244	0	1
Cotton	0.977	0.113	0	1
All plots of target crops	0.825	0.356	0	1

Source : Authors, based on PRePoSAm survey

Table 5. Effects of fertilizer subsidy on outcome variables, fixed effect model

Variables	Total fertilizer applied(kg/ha) coeff		Yield (kg/ha) coeff		Quantity of all crops sold (kgs) coeff		Target crop income (FCFA) coeff	
Paper voucher=1	12.7	**	403	***	4.25	***	0.604	***
	(6.02)		(114)		(0.127)		(0.175)	
Paper and evoucher=1	21.7		905		1.723	*	0.001	
	(46.3)		(756)		(978)		(1.353)	
Plot size (ha)	-5.11	***	-49.3	***	0.043	***	0.072	***
	(0.672)		(12.0)		(0.014)		(0.020)	
Manure=1	-0.005		-0.048		0.000		0.000	
	(0.003)		(0.06)		(0.000)		(0.000)	
Plot age (yrs)	0.364	***	5.93	**	0.014	***	0.015	***
	(0.124)		(2.39)		(0.003)		(0.004)	
Intercropped=1	-1.50		38.4		-0.494	***	-0.553	***
	(5.33)		(110)		(0.113)		(0.156)	
rainfed	-103	***	-1132	***	0.019		-0.097	
	(12.1)		(212)		(0.256)		(0.354)	
soil type dummies	ns		ns		ns		ns	
relief dummies	ns		ns		ns		ns	
Constant	217	***	2034	***	3.59	***	6.07	***
	(19.0)		(335)		(0.402)		(0.557)	

n=9194 plots and 2398 households. *=sig at 10%, **=sig at 5%; ***=sig at 1%
Sorghum yields not measured. Individual soils and relief dummies significant in some cases but not as a group. All crops sold and target crop income (gross revenues) are in logarithms because they are skewed. Source : Authors, based on PRePoSAm survey.

Table 6. Average treatment effects on outcome variables, all crops and by target crop

	Total fertilizer applied (kg/ha)	Yield (kg/ha)	Target crop income (1000FCFA)	Quantity of all crops sold (kgs)
All crops	67.1***	533***	301***	4330***
N	9172	5612	4311	9180
Millet	9.69***	ns	23.5***	ns
N	1977	777	561	1978
Sorghum	ns		ns	3340***
N	1577		223	1578
Rice	74.6***	1040***	484***	6250***
N	2712	2114	1859	2714
Maize	82***	294**	51.3	3500
N	1511	1346	337	1513
Cotton	51.6**	ns	ns	ns
N	1395	1375	1331	1397

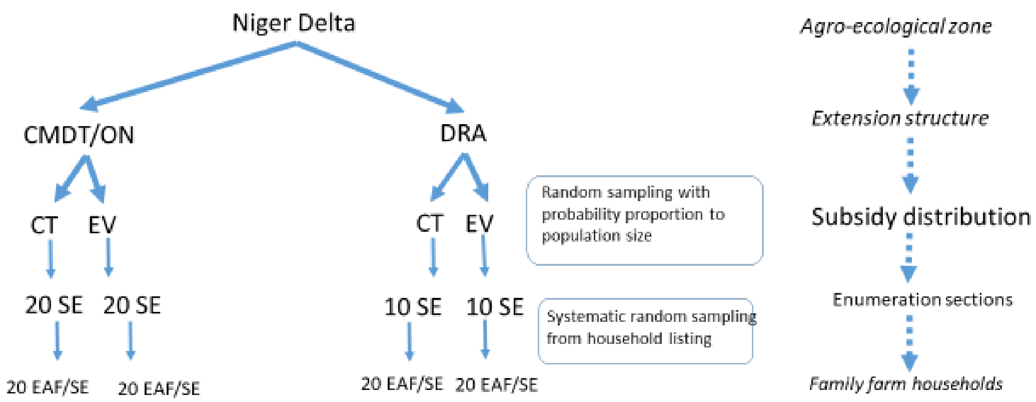
*=sig at 10%, **=sig at 5%, ***=sig at 1%, ns=not significant. *N* is number of observations by crop. Source : Authors, based on PRePoSAm survey.

Table 7. Balancing property test (values of t-test statistic)

	Block 1 [0, 152.5]		Block 2 [152.6, 230.8]		Block 3 [231, 326]	
	Before	After	Before	After	Before	After
Paper voucher	29.199	**5.5976**	-22.483	**-17.201**	-11.293	**-4.7639**
Intercrop	-25.285	**-8.7802**	17.907	**13.449**	11.977	**8.3389**
Plot size	-0.82307	-0.27501	0.52352	-1.6181	0.49195	-1.8039
Plot age	-1.1385	0.54842	0.81834	0.08406	0.5552	-0.10716
Loamy soil	1.8102	1.7442	-3.49	-2.79	2.0248	0.90898
Clay soil	7.4244	-1.6337	-0.73846	**8.1209**	-9.7519	1.7398
Gravelly soil	0.58609	**2.9371**	-3.9465	**-8.4032**	4.4006	0.13617
Plain	0.1967	1.2136	-1.6363	-1.8293	1.8915	0.00949
Plateau	-0.27835	0.50634	-1.215	-3.042	2.0173	0.57023
Slight slope	-1.2807	-1.4738	1.7458	1.0576	-0.4721	0.01957
Steep slope	1.4185	1.3314	-2.3959	**-2.6371**	1.1371	-0.18815
Nonfarm income	0.02955	-2.1498	0.9528	**2.0159**	-1.3093	-0.29902
manure	2.7545	1.288	-3.0107	**-2.1918**	0.02651	0.02725
Adult males	-6.1146	-**4.1523**	5.362	**2.1808**	1.6905	-1.3573
Adult females	-5.0478	**-3.981**	4.6636	**3.1109**	1.0831	0.05134
Membership	5.1893	**5.0672**	-8.3033	-10.846	3.5206	0.04364
Farm area	-11.405	**-5.4755**	5.837	0.47449	8.6347	**3.022**
Manager age	2.9795	1.2248	-3.6352	-3.579	0.53056	1.1952
Head of household	8.8147	**3.269**	-7.2371	-3.8411	-3.0773	-0.59923
Head of workshe	-2.7984	0.09905	2.7769	0.33502	0.3474	-1.3354

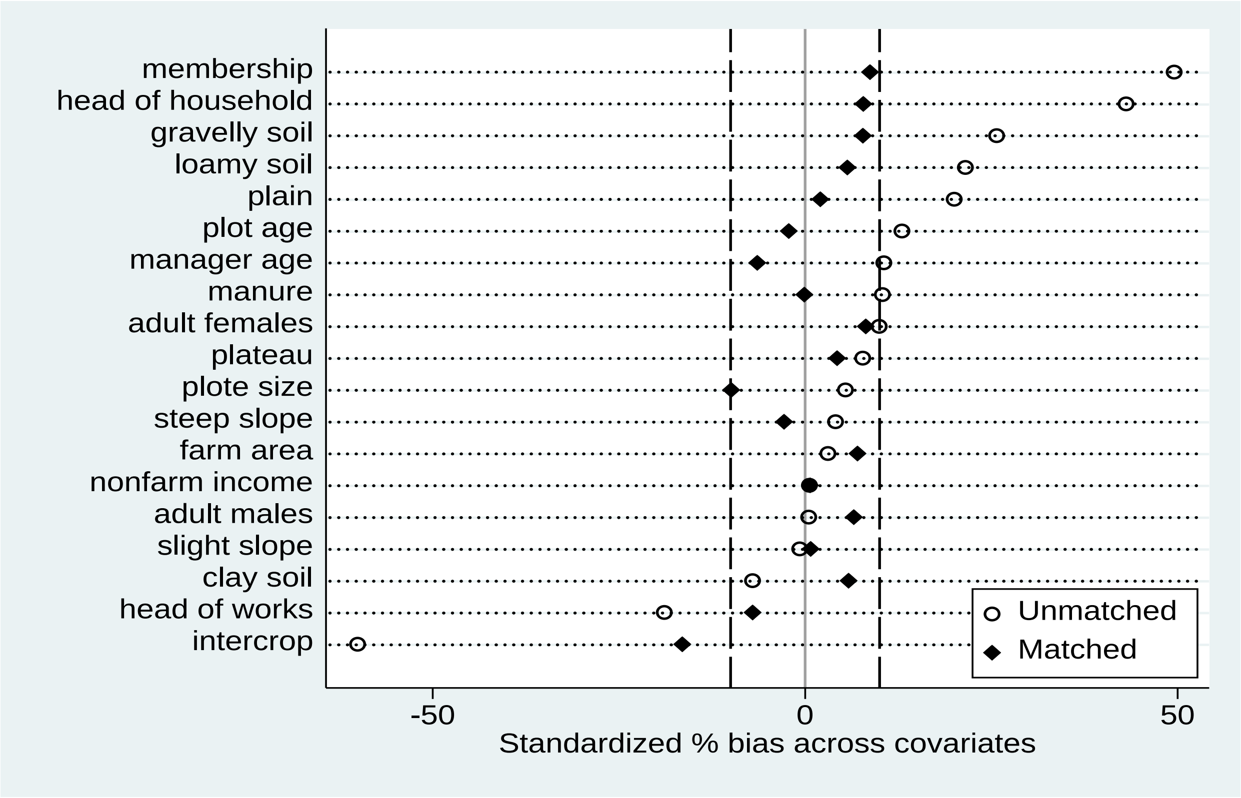
Source : Authors, based on PRePoSAm survey.

Figure 1. Sampling scheme



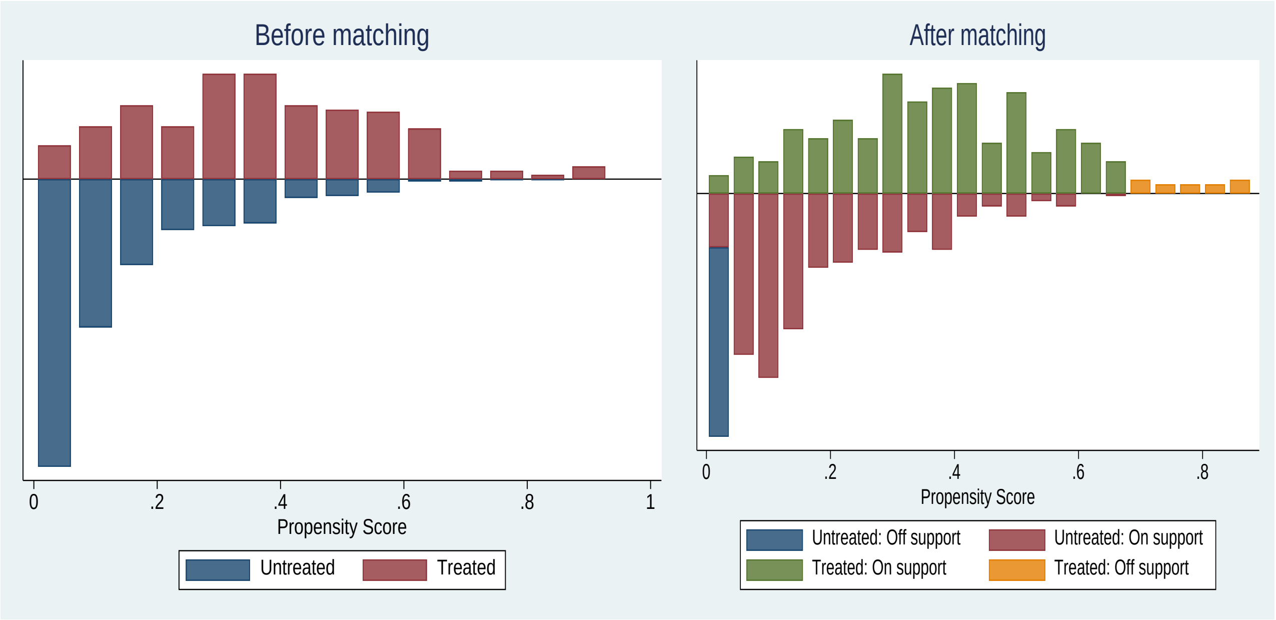
Source: Authors.

Figure 2. Balance quality of binary PSM



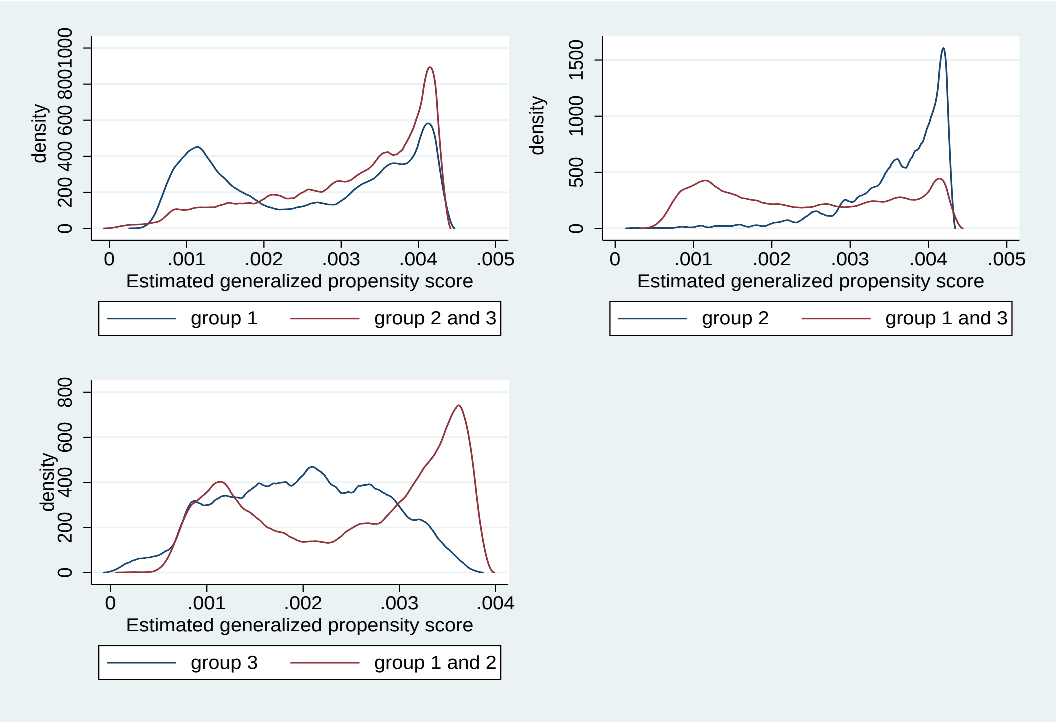
Source : Authors, based on PRePoSAM survey.

Figure 3. Propensity score distribution before and after matching



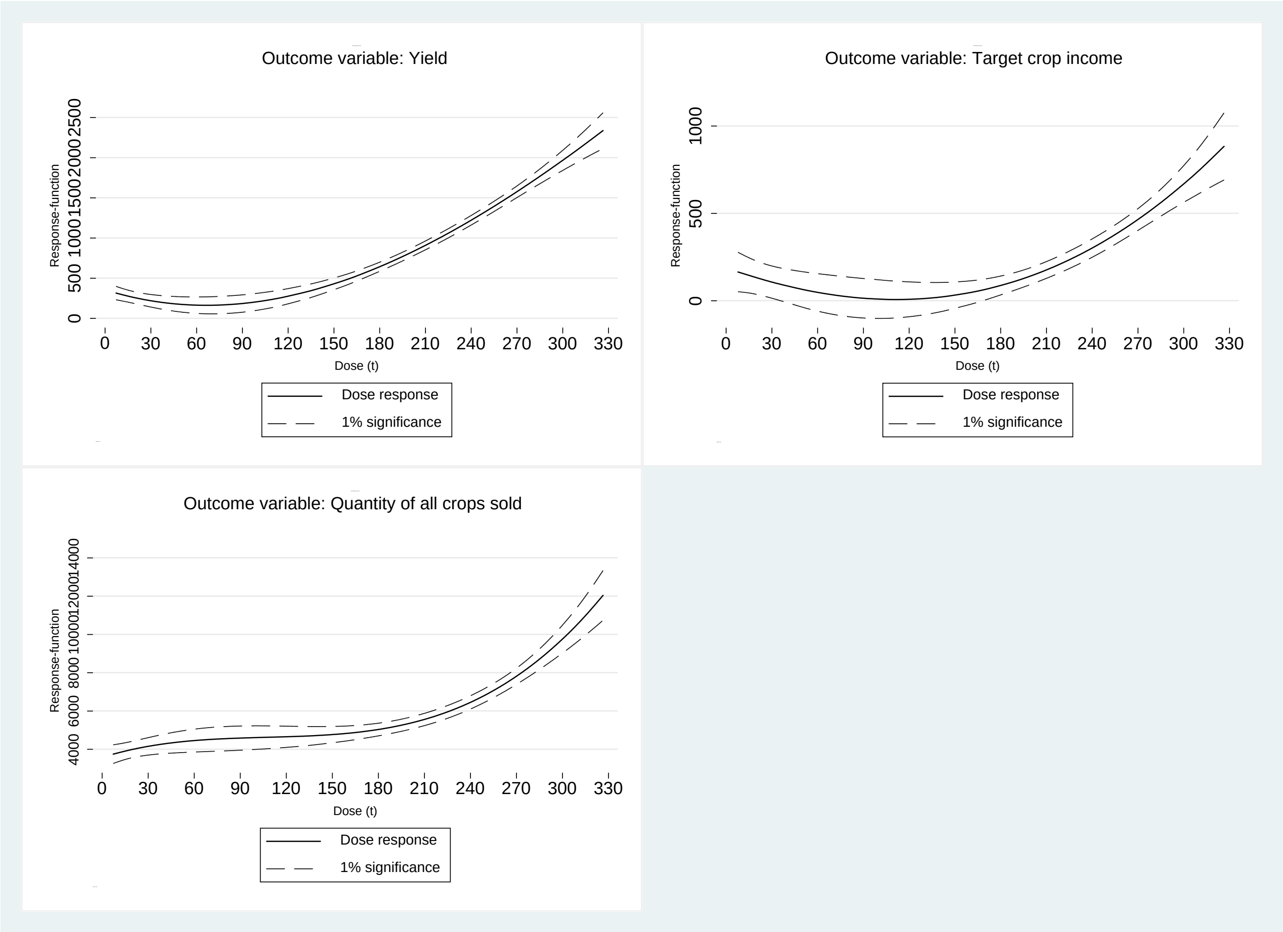
Source : Authors, based on PRePoSAM survey.

Figure 4. Common support region for generalized propensity score



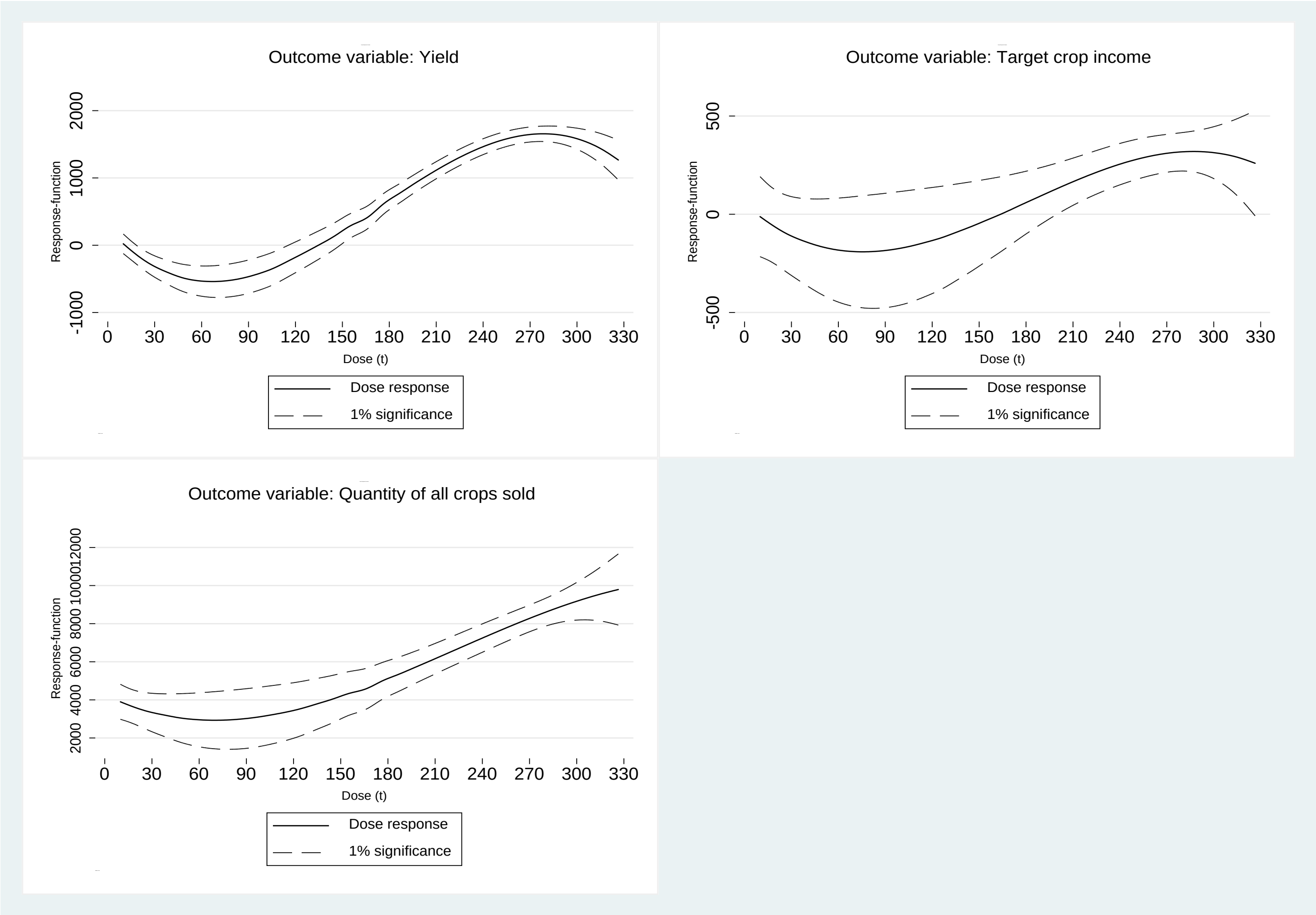
Source : Authors, based on PRePoSAM survey.

Figure 5. Dose-response graphs for all crops



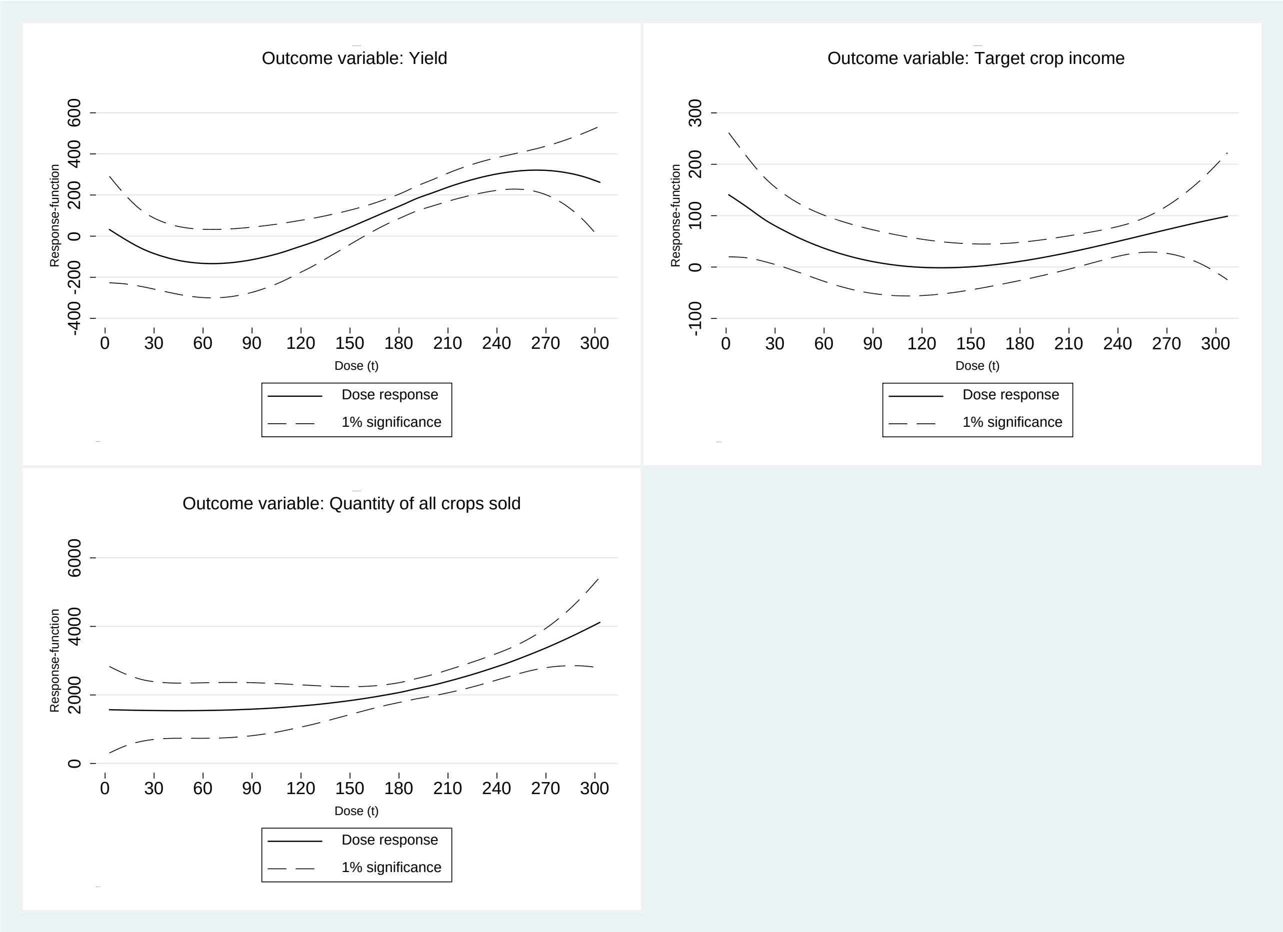
Source : Authors, based on PRePoSAM survey.

Figure 6. Dose-response graphs for rice



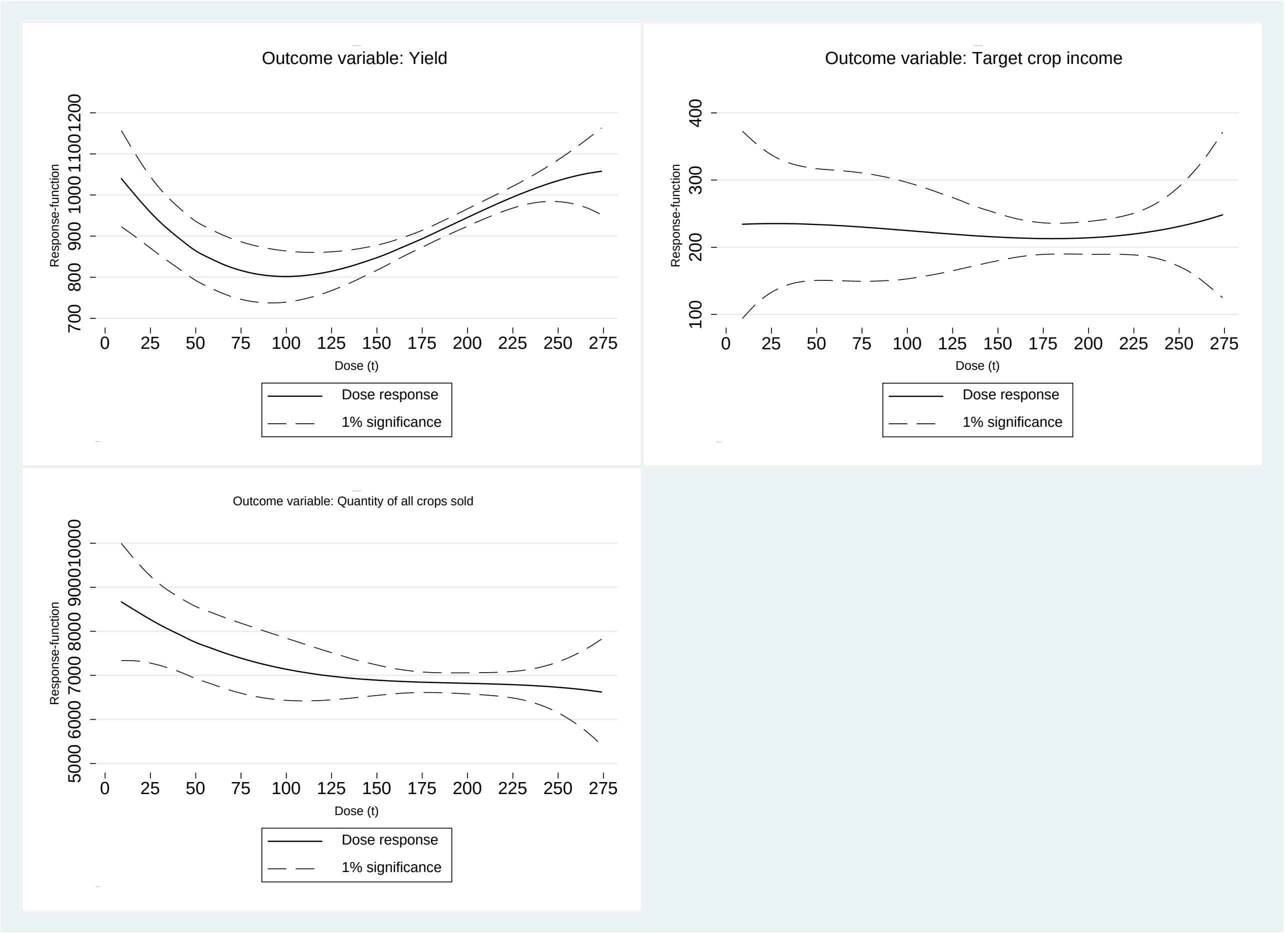
Source : Authors, based on PRePoSAM survey.

Figure 7. Dose-response graphs for maize



Source : Authors, based on PRePoSAM survey.

Figure 8. Dose-response graphs for cotton



Source : Authors, based on PRePoSAM survey.

APPENDIX

Table A1. Balancing test binary treatment

	Unmatched				Matched				
Variable	Treated	control	%bias	p-value	Treated	control	%bias	p-value	%reduct bias
Intercrop	1.05	1.25	-60.10	0.00	1.18	1.25	-19.70	0.01	67.20
Plot size	2.34	2.22	5.40	0.24	2.00	2.23	-9.90	0.12	-83.80
Plot age	18.71	16.99	13.00	0.01	16.69	16.98	-2.20	0.74	83.00
Loamy soil	0.17	0.10	21.40	0.00	0.12	0.10	5.60	0.36	73.70
Clay soil	0.42	0.45	-7.00	0.15	0.48	0.45	5.80	0.38	17.20
Gravelly soil	0.07	0.02	25.70	0.00	0.04	0.02	7.80	0.14	69.80
Plain	0.70	0.61	20.00	0.00	0.62	0.61	2.00	0.77	89.80
Plateau	0.01	0.00	7.70	0.18	0.01	0.00	4.30	0.47	44.50
Slight slope	0.15	0.16	-0.70	0.88	0.16	0.15	0.70	0.91	-1.40
Steep slope	0.01	0.01	4.10	0.44	0.01	0.01	-2.80	0.60	30.30
Nonfarm income	2.70E+05	2.70E+05	5.00E-01	9.18E-01	2.70E+05	2.70E+05	0.60	0.92	-23.20
Manure	125.16	30.70	10.40	0.11	29.80	30.88	-0.10	0.96	98.80
Adult males	4.23	4.22	0.50	0.92	4.39	4.22	6.50	0.33	-1203.70
Adult females	4.80	4.49	10.00	0.04	4.74	4.49	8.10	0.22	18.30
membership	11.49	6.54	49.50	0.00	7.45	6.57	8.70	0.13	82.40
Farm area	12.65	12.26	3.10	0.58	13.15	12.27	7.00	0.34	-129.40
Manager age	44.14	42.81	10.60	0.04	41.95	42.77	-6.40	0.33	39.10
Head of household	0.67	0.46	43.10	0.00	0.50	0.46	7.80	0.26	81.90
Head of works	0.32	0.41	-18.90	0.00	0.38	0.41	-7.00	0.30	62.70

Source : Authors, based on PRePoSAm survey.

Table A2. Rosenbaum sensitivity all crops (Upper-bound significance level p-value)

Gamma	fertilizer	yield	all crops sales	target crop incles
1	0.00	0.00	0.00	0.00
1.1	0.00	0.00	0.00	0.00
1.2	0.00	0.00	0.00	**0.36**
1.3	0.00	0.00	0.00	0.96
1.4	0.00	0.00	0.00	1.00
1.5	0.00	0.09	0.00	1.00
1.6	0.00	**0.71**	0.00	1.00
1.7	0.00	0.99	0.00	1.00
1.8	0.00	1.00	0.00	1.00
1.9	0.00	1.00	0.00	1.00
2	0.00	1.00	0.00	1.00

Source : Authors, based on PRePoSAm survey.

Table A3. Rosenbaum sensitivity millet (Upper-bound significance level p-value)

Gamma	fertilizer	yield	all crops sales	targetsales
1	0.00	0.00	0.00	**0.93**
1.1	0.00	0.00	0.00	0.99
1.2	**0.12**	0.01	0.00	1.00
1.3	0.53	0.06	0.00	1.00
1.4	0.89	**0.18**	0.00	1.00
1.5	0.99	0.36	0.00	1.00
1.6	1.00	0.58	0.00	1.00
1.7	1.00	0.76	0.00	1.00
1.8	1.00	0.88	0.00	1.00
1.9	1.00	0.95	0.00	1.00
2	1.00	0.98	0.00	1.00

Source : Authors, based on PRePoSAm survey.

Table A4. Rosenbaum sensitivity sorghum (Upper-bound significance level p-value)

Gamma	fertilizer	yield	all crops sales	targetsales
1	**1.00**		0.00	0.00
1.1	1.00		0.00	0.00
1.2	1.00		0.00	0.00
1.3	1.00		0.00	0.00
1.4	1.00		0.00	0.00
1.5	1.00		0.00	0.00
1.6	1.00		0.00	0.00
1.7	1.00		0.00	0.00
1.8	1.00		0.00	0.00
1.9	1.00		0.00	0.00
2	1.00		0.00	0.00

Source : Authors, based on PRePoSAm survey.

Table A5. Rosenbaum sensitivity rice (Upper-bound significance level p-value)

Gamma	fertilizer	yield	all crops sales	targetsales
1	0.00	0.00	0.00	0.00
1.1	0.00	0.00	0.00	0.00
1.2	0.00	0.00	0.00	0.00
1.3	0.00	0.00	0.00	0.00
1.4	0.00	0.00	0.00	0.07
1.5	0.00	0.00	0.00	**0.40**
1.6	0.00	0.00	0.00	0.80
1.7	0.00	0.00	0.00	0.97
1.8	0.00	0.00	0.00	1.00
1.9	0.00	0.00	0.00	1.00
2	0.00	0.00	0.00	1.00

Source : Authors, based on PRePoSAm survey.

Table A6. Rosenbaum sensitivity maize (Upper-bound significance level p-value)

Gamma	fertilizer	yield	all crops sales	targetsales
1	0.00	0.00	0.00	**0.22**
1.1	0.00	0.00	0.00	0.48
1.2	0.00	0.00	0.00	0.72
1.3	0.00	0.00	0.00	0.88
1.4	0.00	0.01	0.00	0.96
1.5	0.00	0.09	0.00	0.99
1.6	0.00	**0.36**	0.00	1.00
1.7	0.00	0.70	0.00	1.00
1.8	0.00	0.92	0.00	1.00
1.9	0.00	0.99	0.00	1.00
2	0.00	1.00	0.00	1.00

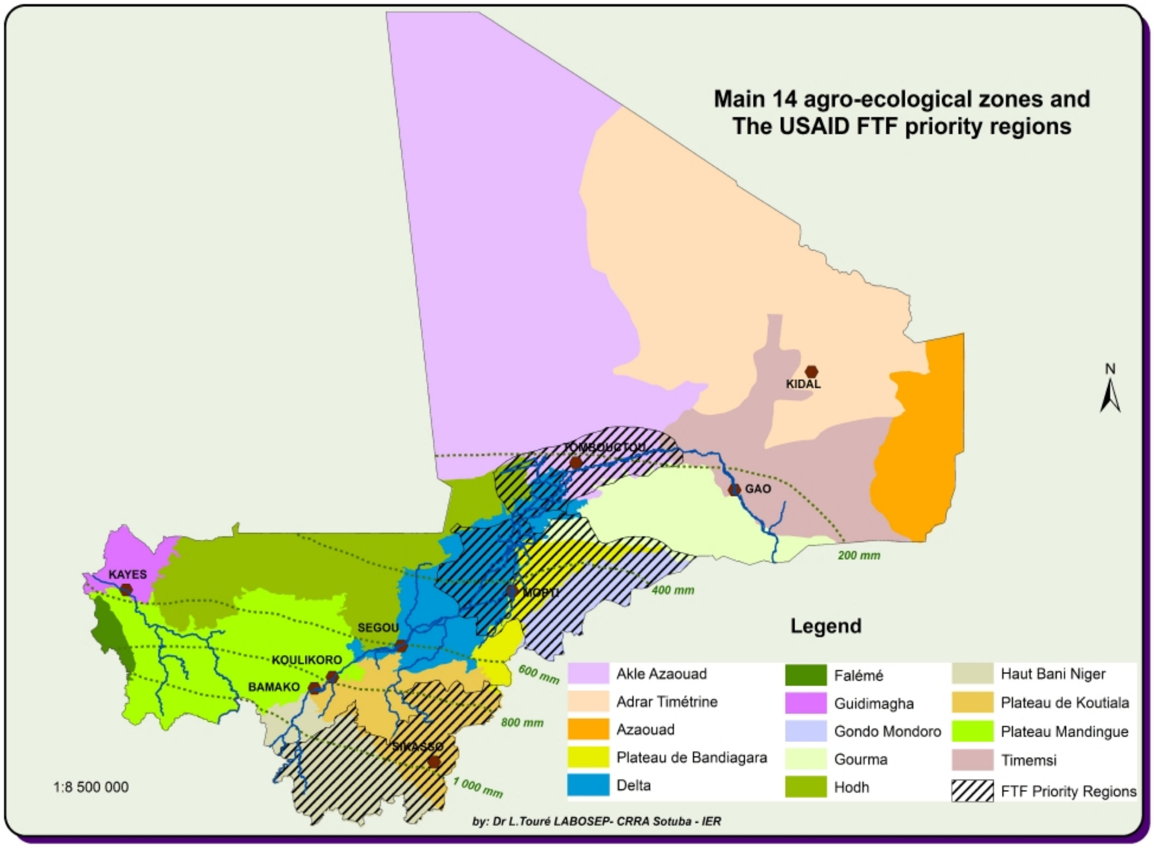
Source : Authors, based on PRePoSAm survey.

Table A7. Rosenbaum sensitivity cotton (Upper-bound significance level p-value)

Gamma	fertilizer	yield	all crops sales	targetsales
1	0.00	0.00	0.00	**0.67**
1.1	0.00	0.00	0.00	0.97
1.2	0.00	0.00	0.00	1.00
1.3	0.00	0.00	0.00	1.00
1.4	0.00	0.00	0.00	1.00
1.5	0.00	0.00	0.00	1.00
1.6	0.00	0.00	0.00	1.00
1.7	0.00	0.00	0.00	1.00
1.8	0.00	0.00	0.00	1.00
1.9	0.00	0.00	0.00	1.00
2	0.00	0.00	0.00	1.00

Source : Authors, based on PRePoSAm survey.

Figure A 1. Map showing the agroecological zones of Mali and USAID Feed the Future priority regions.



Source: Dr. L. Touré, Labosep, Sotuba Research Station, Institut d'Economie Rurale