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Impacts of modifying Malawi's farm input subsidy programme targeting

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Contents

Tables

Figures

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Abstract

The Farm Input Subsidy Programme (FISP) in Malawi was introduced in the 2005/2006 season against a background of bad weather affecting production and resulting in prolonged food shortages. Vouchers are distributed, empowering eligible farmers to exchange them for fixed quantities of inputs at subsidized prices, with the primary purpose of increasing food self-sufficiency of resource-poor smallholder farmers and income through enhanced maize production. Since its inception, there has been a debate at national level about whether the FISP’s potential has been fully exploited with policy makers exploring options to improve the effectiveness of the programme. Proposals, among others, include enhancing productivity by targeting efficient and productive farmers. In this paper, we evaluate the impact of this proposed change to the existing FISP design and implementation mechanisms by utilizing two waves of the Living Standards Measurement Survey - Integrated Surveys on Agriculture (LSMS-ISA) survey merged with historical climate data. We estimate how the demand for agricultural inputs varies according to a variation in the targeting criteria and identify more efficient farmers that should be eligible for the FISP. We observe a significant mismatch between voucher recipients and efficiency; at the district level, for example, most vouchers go to districts characterized by less efficient production. Better targeting criteria result in a modest increase in food expenditure ranging from 0.27% to 0.8% and maize production from 0.2% to 1.3%. The concerns emerging on the equity of the programme are discussed together with some suggestions for spatially diversifying the structuring of the policy and incentivizing crop diversification strategy.

Keywords: Input subsidies, targeting, efficiency, QUAIDS, cash transfer, Malawi, Africa

JEL codes: Q12, Q18, O12

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1 Introduction

Historically, the use of agricultural inputs has been low in sub-Saharan African (SSA) countries and remains the lowest worldwide (Otsuka and Larson, 2012). Among the causes of low use, structural market frictions, such as high transportation costs, price fluctuations or a weak delivery system, play a major role in preventing farmers from having access to quality inputs or credit for financially sustaining modern agriculture (Dercon and Gollin, 2014; Collier and Dercon, 2014; Liverpool and Winter-Nelson, 2010; Conley and Udry; 2010). Agricultural input subsidies have been often utilized in SSA to develop the agricultural systems and increase food security by modifying relative prices and incentivize farmers to increase the use of fertilizers and hybrid/modern seeds (Holden and Lunduka, 2014; Jayne and Rashid, 2013; Kelly et al., 2003; Crawford et al., 2003).

In the particular context of Malawi, the Farm Input Subsidy Programme (FISP) was introduced in the 2005/2006 season, against a background of weather shocks affecting production and resulting in prolonged food shortages and high input prices in the absence of soft farm input loans for smallholders. The primary purpose of the programme was to increase access of resource-poor smallholder farmers to improved agricultural farm inputs in order to achieve food self-sufficiency and increase income through enhanced maize production. To this end, vouchers are distributed throughout the country, thereby empowering eligible farmers to redeem them at subsidized prices in exchange for fixed quantities of improved maize seeds or chemical fertilizers.

In general, while maize productivity shifted on average from 1480 kg/ha in 2006 to 2100 kg/ha in 2013 and the prevalence of undernourishment decreased from 27% to 20.8% (FAOSTAT, 2015), there is doubt whether such improvements have been driven by FISP and concerns about the stability of food security as well as the distributional impacts of the programme itself. There has been increasing debate at national level on the FISP potential, with many thinking this may have not been fully exploited yet. In particular, the targeting criteria used to define eligible farmers have been highlighted as one of the main structural crux to review in order to improve programme effectiveness and equity (Chibwana et al., 2012; Dorward and Chirwa, 2011). Eligibility for obtaining vouchers was originally based on the status of individual vulnerability. Targeted farmers had to be smallholders and/or female-headed households that were severely cash constrained or had limited wealth endowments (Lunduka et al., 2013). These potentially “productive poor” have been defined as farm households with the necessary land, labour and skills to use the subsidized inputs, but without the financial capital to purchase inputs at commercial prices (MoAFS, 2008).

Nevertheless, the disregarding of these targeting guidelines at local level often led to confusion in allocation procedures and widespread ambiguity as to the real impact of the targeting criteria. In fact, many studies have pointed to the FISP being relatively more allocated to rural middle-income or higher-income households at the expense of poor productive farmers (Kilic et al., 2013; Ricker-Gilbert et al., 2011; Fisher and Kandiwa, 2013). Whether the aforementioned criteria are actually able to identify efficient farmers remains to be discussed, as well as whether ultra-poor farmers can really exploit the potential benefits arising from receiving vouchers. For farmers who are severely cash constrained, the purchase of subsidized inputs may not be seen as a feasible option (Croppenstedt et al., 2003) and chances are that farmers sell the vouchers in exchange for cash they can use to satisfy basic needs such as food (Chibwana et al., 2012).

Within this context, targeting farmers without conditions attached can undermine the overall efficiency of the subsidy programme because the objective of increasing agricultural production falls short of the potential frontier that could be achieved if those who can maximize returns by necessarily high-income households. Thus, while the objective should still be to help vulnerable farmers, among these, differences in the productive potential can be identified and utilized to enhance the overall efficiency of the FISP (Dorward and Chirwa, 2011). Yet to preserve the equity of the programme, excluded ultra-poor farmers will need to be compensated with alternative safety-net programmes. The compensation should be given in a way that helps them build human and capital assets to improve their current status (Sabates-Wheeler and Deveraux, 2010; Ellis and Maliro, 2013). On the other hand, because of the potential crowding out of the commercial sector, it should be considered whether efficient farmers could substitute part of the share of purchased commercial inputs with the subsidized ones (Ricker-Gilbert et al., 2011).

The opportunity costs of the FISP have been extensively studied (e.g., Dorward et al., 2009; Arndt et al., 2016; Lunduka et al., 2013), including the effect on land allocation, crop and dietary diversification (e.g., Chibwana et al., 2012; Jones et al., 2014) and the impact on the rural gender gap (e.g., Fisher et al., 2014). Less is known about how to reduce such opportunity costs by means of increasing the efficiency of the programme given the high share of budget expenditure devoted to the programme. In particular, we have no knowledge of studies that *ex-ante* investigate whether the FISP effectiveness can be improved by changing the targeting criteria. While the outcome of such improvement has been hypothesized by previous studies (e.g., Lunduka et al., 2013; Jayne and Rashid 2013; Chibwana et al., 2012), a rigorous empirical evidence is missing. Thus, we try to bridge this research gap by also providing policy suggestion on the merits of implementing a modified version of FISP and accounting for distributional impacts.

In this paper, we investigate the impact of adjusting the FISP targeting criteria to favour inclusion of the more efficient farmers. We also account for the equity of the proposed targeting policy by analysing the effects on ultra-poor farmers. In order to address these issues three methodological steps are implemented using two rounds of the Living Standards Measurement Survey - Integrated Surveys on Agriculture (LSMS-ISA) conducted in Malawi in 2010/2011 and 2012/2013. First, expenditure and price elasticities for agricultural inputs are obtained after estimating a simultaneous and multi-stage demand system (through a QUAIDS model) with a consumption quota, which are key elements in evaluating how different targeting criteria affect input consumption. These elements have not been properly included in previous empirical literature on FISP and are more likely to affect the policy evaluation. Second, marginal effects of inputs on maize production, socio-economic characteristics of farmers who are more efficient, and agro-ecological conditions that affect the efficiency distribution are identified (using a stochastic frontier framework) in order to depict an ideal profile of “winner” farmers who seem ideal candidates for overall FISP efficiency enhancement. This approach allows to obtain a clear ranking of farmers who are efficient in exploiting the subsidized inputs and help policy makers for better targeting of FISP beneficiaries. Third, both analyses allow for policy simulations at spatially disaggregated micro scale, in which new eligible farmers and those losing the eligibility face a new vector of prices for agricultural inputs and from which we can recover a welfare measure, which should be highly informative to policy makers of the convenience of applying the desired targeting variation.

While the FISP policy design seems well studied, our results identify both potential gaps in the current programme implementation and provide an evaluation for outcomes based on alternative FISP targeting scenario. In this sense, the analysis could be highly informative not only for Malawian policy makers, but also for other countries looking at programmes such as FISP with the intention to emulate them to push agricultural modernization and improve food security.

The paper is organized as follows. The next section presents an overview of farm input subsidy programme design in SSA as well as in Malawi. The conceptual framework that motivates the analysis is presented in Section 3, whereas Section 4 illustrates the empirical methodology and data. Section 5 illustrates results. Discussion and policy implications are presented in Section 6.

2 Overview of farm input subsidy programme (FISP)

2.1 FISP targeting design in Sub-Saharan Africa

Three broad types of programme design for farm input subsidies can be distinguished in SSA. In the mid-1990s, demonstration packages were used and large scale multi-year programmes that were either targeted (in East & Southern Africa) or universal (in West Africa) were subsequently introduced. At the beginning of the 2000s, subsidies were implemented as demonstration packs in several countries with the main objective of raising awareness of the use of fertilizers and demonstrating their utility to smallholder farmers. Demonstration packs were programmes implemented on a regular basis (one to a few years) which distributed small quantities of free or heavily subsidized fertilizer to a significant number of farmers, generally as part of a package involving complementary inputs and training/extension. Examples include two demonstration packages implemented in Malawi, the Starter Pack (universal, rationed subsidy) and Targeted Input Programme (targeted version of the Starter Pack), or the Sasakawa Global Initiative programmes implemented in the mid-1990s to early 2000s in several African countries (Druilhe and Barreiro-Hurlé, 2012). The second approach involves subsidies to boost national production and productivity by making inputs more affordable on a very large scale and over a longer time period. These objectives are possibly combined with a clear poverty reduction objective (Wanzala-Mlobela *et al*., 2011). There are two groups of subsidies depending on whether these are targeted to a specific farmer category, crop and region or are applied more or less universally.

The targeted subsidies include the five recent programmes implemented in East and Southern Africa: Kenya, Malawi, Rwanda, Tanzania and Zambia. These subsidies correspond to what is understood as a new model of pro-poor, targeted and market-friendly "smart" subsidies. The example of Malawi is telling of the evolution of African programmes from demonstration packs at the beginning of 2000s to the larger but more targeted subsidy programmes in the late 2000s. The objectives of the Malawian schemes evolved from social protection for vulnerable households with the first programme (Starter Pack) to kick-starting agricultural production with the second (Targeted Input Programme) and to national food production and self-sufficiency objectives in the third and so far final phase (FISP). Targeted programmes have in common their large scale in terms of number of beneficiaries (e.g. 2.5 Million in Kenya), time frame (multi-year, e.g., 10 years in Zambia), coverage (nation-wide), and implementation arrangements (targeted and/or using vouchers). As a result, subsidized sales cover a significant share of total fertilizer market (e.g. up to 42% in Malawi) and they absorb a significant part of total public expenditure in agriculture (e.g. 60% in Malawi, up to 50% in Tanzania and 40% in Zambia) (Druilhe and Barreiro-Hurlé, 2012).

On the other hand, West Africa (Burkina Faso, Ghana, Mali, Nigeria and Senegal) are implementing fertilizer subsidies, which seem to revert to universal (untargeted) price subsidies, with targeting of specific crops only (rather than farmers). In four cases out of five, they have been implemented following the food and fertilizer crisis of the late 2000s. As an example, in 2008, in response to the food and fertilizer price crisis, Mali launched a fertilizer subsidy targeted at rice (which was extended thereafter to other crops). Under this scheme, all farmers growing the targeted crops are eligible and receive fertilizers in proportion to the size of their planted area. Implementation is quite complex and involves a paper form ("*caution technique*") indicating the number of bags each farmer is eligible for and which is used both at the time of fertilizer allocation and reimbursement of suppliers/dealers. Funding, as in other recent schemes, is largely national (e.g. Burkina 100% in 2008 and 2010; Mali

70%). In addition to the focus on food crops, in Burkina Faso, Mali and Ghana, plantation farmers have also received subsidies. The system seems to function better than procurement and distribution through the state deconcentrated offices (Burkina Faso) or through distributors under contract with the state (Mali), but it only benefits farmers who are already affiliated with the companies. In the case of Burkina Faso and Mali, cotton companies/offices provide the fertilizer in the form of input credit to cotton farmers. In Burkina Faso, credit to cotton farmers is extended to fertilizers used for cereals to avoid the typical diversion of cotton fertilizer to food crops (cereals).

2.2 FISP design and implementation in Malawi

The Malawian FISP started within the context of the national strategy for the development of agriculture and targeted almost half of the rural population by aiming to improve smallholder farmers' access to agricultural inputs, boost crop maize productivity and promote food self-sufficiency. Eligibility to the FISP guarantees that different types of vouchers that entitle farmers to agricultural inputs at subsidized prices will be received from Agricultural Development and Marketing Corporation (ADMARC) outlets or from Farmers Fertiliser Revolving Fund of Malawi (SFFRFM). The types of voucher have changed throughout the years but as of the 2009 season, only four types exist, allowing beneficiaries to redeem vouchers for: (i) a 50-kg bag of basal maize fertilizer (NPK-23:21:0+4s or Chitowe), (ii) a 50-kg bag of urea fertilizer, both for a base price of MK500, (iii) either a 5-kg bag of hybrid maize seed or a 10-kg bag of open pollinated varieties (OPV) maize seed for a price up to MK150, and (iv) a flexy voucher which can be exchanged for a free 1 kg bag of legumes or groundnut seeds.

Officially, the targeting criteria for voucher eligibility was oriented to the provision of inputs to vulnerable and marginalized smallholders (Lunduka et al., 2013; Dorward et al., 2013), with a formal allocation process structured in three steps. First, the Ministry of Agriculture and Food Security (MoAFS) distributes vouchers at district-level with criteria rewarding those districts with the higher shares of the rural population. Second, the district authority allocates the vouchers across villages. Third, the village traditional authority identifies beneficiary households. Nevertheless, a lack of defined, standardized and structured targeting criteria has been observed with many village focus groups reporting that more coupons are distributed in a district in which a member of the governing party resides or are allocated on payment of a bribe. Moreover, redeeming at prices above the official suggested threshold have been observed (Lunduka et al. 2013).

Under the FISP, the government distributes vouchers to farmers that enable them to purchase a fixed amount of fertilizers (as well as maize and legume seeds) from ADMARC outlets at a fixed price. This quota system with subsidized price works only for farmers receiving the vouchers and forces ineligible farmers, or the eligible ones requiring more inputs than allowed by their fixed quota, to face the current market price and purchase commercial fertilizer from the market. While the FISP has been seen to help vulnerable agricultural households to modernize their farming and cropping activities, some questions emerge about the overall effectiveness of the programme in terms of achieving the intended objectives. The FISP was initially intended to incentivize those farmers who obtain a marginal benefit above the unitary (subsidized) cost of fertilizer such that they can increase their consumption and utilization of inputs more than what is allowed by the quota system. This should in turn bring about overall productivity gains if farmers consuming more fertilizers are also the most efficient in maize production.

3 Conceptual framework

Since the main aim of the FISP is to promote maize production and food security, our objective is to evaluate its impact under different targeting criteria. The impact of changing the targeting will depend on two elements. The first is the variation in the use of agricultural inputs, both by farmers who lose eligibility to the FISP and those who become eligible under the new criteria. The second is how maize production reacts to the resulting changes in the application rates of agricultural inputs by different farmers.

Households organize their expenditure according to basic needs, conditional on their status of vulnerability. They allocate their budget to food and non-food items (Ecker and Qaim, 2011), including expenditure on agricultural inputs, which is vital for their subsistence strategy (Holden et al., 2004, Dzanku et al., 2015). These are factors of the crop production function and contribute to enhancing the self-production of food that ensures both food security and the main source of income of rural households (Reardon et al., 2000; Gómez et al., 2013). In SSA, the expenditure share on agricultural input is very limited and in most cases null given the cash constraint (Otsuka and Larson, 2013). Risk-adverse households rely, for instance, on crop diversification as a substitute strategy to reduce the variability of production with respect to climatic shocks, adverse agro-ecological conditions, pest, diseases and price volatility (Bellon, 2004; Di Falco and Perrings, 2005). When subsidies to inputs are introduced, farmers may increase consumption on agricultural inputs according to their preferences and budget, which is reflected in changes in expenditure and price elasticities. On the other hand, they may not change the amount of fertilizers and seeds purchased, but utilize part of the extra-budget to increase food expenditure (Holden and Lunduka, 2013).

The particular type of subsidies introduced with the FISP is based on a quota system for which the eligible households can obtain just a rationed fixed quantity of inputs at a subsidized price (q_k). If the household needs additional quantities of inputs, these can be bought from commercial retailers at the full market price. Households that face a severe cash constraint and lose their eligibility because the targeting criteria changed are likely to reduce their consumption of agricultural inputs, according to their quota elasticity[1], with effects on crop productivity. Alternatively, they can substitute the subsidized quantities with an equal amount of commercial inputs and modify their budget at the expense of other basic consumption needs. On the other hand, farmers who become eligible due to changes in targeting criteria are likely to reduce the use of commercial inputs because they are replaced by subsidized quantities. Consequently, for newly eligible farmers, total expenditure on agricultural inputs will be reduced and the extra-budget can be used to increase other consumption goods such as food. On the contrary, if they prefer to consume a quantity of inputs (q) above the rationed fixed quantity of inputs at a subsidized price (such that: $q > q_k$), the purchasing of inputs will increase resulting in positive effects on maize production.

However, the response of production to the variation in input rates is not homogenous, being also driven by other factors, which heterogeneously affect households according to their characteristics and endowments (Suri, 2011). In this respect, the empirical evidence identifies several factors of a different nature. For instance, a lack of knowledge in using modern inputs, rainfall variations and structural soil nutrient deficiencies are three important

[1] The percent change in expenditure on commercial inputs for a percent change in the quota level that farmers receive with vouchers.

shifters of the individual production capacity (Tittonel and Giller, 2013; Kijima et al., 2011; Coromaldi et al., 2015; Chavas and Di Falco, 2012). This heterogeneity plays a fundamental role when investigating the effectiveness of different targeting scenarios since it determines the socio-economic and agro-ecological characteristics of farmers for which agricultural inputs are likely to cause a yield response closer to the production possibility frontier. These farmers should be targeted to increase the cost-effectiveness of instruments such as the FISP, whereas other complementary policies such as cash transfer programmes could be successful compensation tools for non-eligible poor farmers (Dorward and Chirwa, 2015). This policy design would balance the potential trade-off between the efficiency and the equity of the new targeting scenarios (Bardhan, 1996).

Based on this framework, a three-step methodology can be implemented. First, we estimate expenditure, price, and quota elasticities of commercial and subsidized agricultural inputs in a demand system framework with a consumption quota for the subsidized inputs. Second, we identify efficient farmers and their socio-economic characteristics by estimating a maize production function in a stochastic frontier approach and obtaining marginal effects of inputs on maize production. The third step envisages the combination of these two outcomes in order to implement micro-simulation of policy scenarios that account for new targeting criteria.

4 Empirical strategy and data

A number of empirical methodologies are used in this paper to evaluate the impact of changes to the existing FISP design and implementation mechanisms. These methodologies are described in this section, although the formal representation of all the empirical methodologies are presented in Appendixes A and B. Also, some of the empirical results are also included in Appendix C.

4.1 Demand system estimation

We estimate expenditure, price and quota elasticities for agricultural inputs by means of a demand system. We build a two-stage budgeting process (Attanasio et al., 2013; Ecker and Qaim, 2011; Gao et al., 1996) where in the first stage households allocate the total expenditure to major basic consumption sets, including food and agricultural inputs. In the second stage, the total expenditure allocated to the latter is allocated to single inputs, namely seeds and organic and chemical fertilizers.

A straightforward econometric approach used to estimate this two-stage separable[2] budgeting process is the almost ideal demand system (AIDS). The AIDS, first introduced by Deaton and Muellbauer (1980) became popular thanks to its consistency with consumer theory (Ryan and Wales, 1999). Subsequently, a quadratic version (QUAIDS) that accounted for non-monotonic response of expenditure shares to total expenditure increase (Banks et al., 1997) was proposed to correct the biased estimates of the original model caused by the potential misspecification of the functional form of preferences (Asche and Wessels, 1997).

Four main econometric challenges need to be addressed to obtain consistent estimates of the QUAIDS in our specific conceptual framework. The first issue is related to the second stage of the QUAIDS and the consumption quota of agricultural input quantities purchasable with the vouchers. In fact, the subgroup of agricultural inputs consists of items that could be purchased both in the market at full price and, depending on voucher ownership, in the FISP outlets by paying a reduced redeeming price for fixed quantities. In our case, we adapt the original QUAIDS function introducing a terms accounting for such quota on subsidized inputs and thereby obtaining quota elasticities.

The second important econometric concern is associated with the endogeneity of total household expenditure in the budget share equations (Blundell and Robin, 1999; Lyssiotou et al., 1999). A potential bias stemming from the correlation between variation in unobservable preferences characteristics and a change in total expenditure shocks driven, for instance, by policy, technological or climatic shocks, could arise if not properly accounted for (Dyer et al., 2006; Mottaleb et al., 2015). The approach proposed for this issue is a Durbin-Wu-Hausman term that augments each share equation with residuals obtained from regressing expenditure on at least one exogenous instruments[3] (Lecoq and Robin, 2015; Mulkay and Khoudmi, 2014; Blundell and Robin, 1999).

The third challenge is related to the zero expenditure on several agricultural input items observed during the second stage of the budgeting process. The issue of censored dependent variables is well known and, as underlined in the literature (Heien and Wessels,

[2] The consistent estimation of a complete system of simultaneous demand equations in a multi-stage setting requires the weak separability of consumer's preferences across consumption groups and sub-group items so as to obtain preferences and elasticities at each stage independently (Edgerton, 1997)
[3] Bootstrapping has been applied to get efficient standard errors (Poi, 2012).

1990), ignoring the determinants of null consumption behaviour could lead to biased results. Shonkwiler and Yen (1999) proposed a two-step procedure with a bivariate probit estimation. In the first step, a binary outcome, equals one if the consumption of an input is positive, and zero otherwise, and is regressed on a vector of socio-demographic covariates. In the second step, the normal probability density and the cumulative distribution of the probit are included in the quota constrained QUAIDS[4]. Here, we propose the probit version of such procedure by also accounting for the sample selection (Yen, 2005; Cappellari and Jenkins, 2006; Jenkins et al., 2006; Tauchmann, 2005) caused by eligibility to the FISP which also represents our fourth challenge (Chibwana et al., 2012). In fact, observing a censored outcome for a commercial agricultural input is likely to be conditioned by receiving the voucher for the same input or not. This incidental truncation is dependent on household structural characteristics that affect their eligibility for the FISP.

4.2 Efficiency and agricultural inputs elasticities estimation

Since early exploration by Aigner et al. (1977), the Stochastic Frontier Production function (SFP) has become popular in empirical research for parametrically estimating technical inefficiency[5]. However, SFP is not exempt from drawbacks such as the imposition of a predetermined functional form and its reliance on strong assumptions regarding the distribution of both inefficiency and idiosyncratic error terms. Based on the rate of inputs utilized, the inefficiency can be defined in terms of the distance between the farmer’s output, which is, in our case, represented by its maize yield and a frontier benchmark evaluated on the sample where the individual is observed. As illustrated in Appendix B, two elements need to be estimated: first, a SFP over which the inefficiency of the farmers is ranked and from which we obtain the marginal impacts of agricultural inputs on maize production; second, a one-sided error term that includes both the technical inefficiency and its drivers (Liu and Myers, 2009)[6].

This framework allows for explicit modelling the error term through a vector of exogenous variables that influence farmer inefficiency. We pursued this methodology for addressing the research questions as it allows identifying the characteristics of more efficient farmers and provide straightforward elements of classification to policy makers to set the group of farmers worth to be targeted in an alternative targeting scenario. Moreover, an additional feature that is particularly relevant to our aim is the ability to generate an individual and strictly positive household efficiency score (Jondrow et al., 1982) which is used to rank households according to their efficiency score level.

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[4] Yen (2002) underlines how the deterministic part of the share equations does not add to unity under the censoring and so error terms do not add up to zero. The adding up restriction is thus not valid and the procedure of estimating n-1 equation is not necessary.

[5]The limitations of this econometric approach are mainly represented by the imposition of a predetermined functional form and the assumptions regarding the distribution of both inefficiency and idiosyncratic error terms.

[6] When panel data are available, we can consistently estimate the stochastic frontier by overcoming many restrictive distributional assumptions required in cross-sectional models (Schmidt and Sickles, 1984). A first specification for time-varying inefficiency is due to Kumbhakar (1990) and following extensions[6] of which the model by Battese and Coelli[6] (1995) is of particular interest since, among others, it allows for modelling of the time-variant inefficiency error component term, u_{ht}, as a truncated normal distribution with the mean μ_{ht}, in order to account for the heteroscedasticity, the variance σ_{uh}^2 (Hadri, 1999), parametrized though a vector of unknown parameters γ that express the impact on inefficiency generated by a vector of exogenous variables z_{ht} such as climatic shocks, agro-ecological factors and other individual socio-economic characteristics (Wang, 2002). A limitation of these models lies in the common intercept α across observations. One approach to overcoming this issue is based on a true fixed effect or a true random effect (Greene; 2005).

4.3 Policy scenarios and effects

We estimate the impact of a new allocation of vouchers based on the production efficiency criteria by utilizing both elasticities obtained from QUAIDS and the marginal effects from the stochastic frontier. In particular, we verify how the new policy influences the variation in maize production and the variation in food expenditure over the baseline case represented by actual voucher distribution either for the HHs identified as being efficient and, then, eligible according to new criteria and for the inefficient ones who lose their eligibility status. The average percentage variation of food expenditure at national level is defined as:

$$dW^{food} = (L + [\sum_{k=1}^{r}(\Delta q_k)p_k + \sum_{\iota=1}^{n}\sum_{k=1}^{r}(\Delta q_k)p_k \cdot z_{\iota k}]) \cdot \eta_{food},$$

where L is a lump-sum compensation greater than zero if provided by the policy, Δq_k is the variation of redeemed quantities of agricultural inputs occurring after the new allocation of vouchers, p_k is the redeeming price, $z_{\iota k}$ is the quota elasticity and η_{food} is the unconditional expenditure elasticity of the “food” category estimated at the first stage of QUAIDS. Then, while the first term within the square parenthesis represents the income variation due to the change in expenditure on redeeming vouchers, the second term represents the variation in income due to the substitution between commercial and subsidized inputs expenditure.

The variation of maize production is instead given by:

$$dy = \sum_{x=1}^{X}\left[\sum_{k=1}^{r}(\Delta q_k) + \sum_{\iota=1}^{n}\sum_{k=1}^{r}(\Delta q_k) \cdot z_{\iota k}\right] \cdot \beta_x^y$$

where β_x^y represents the marginal effect of the agricultural input x (without distinguishing between commercial and subsidized) on maize production y as obtained by the stochastic frontier.

4.4 Data description

In this study, we employ two rounds of the Malawi LSMS-ISA survey which was conducted by the Central Statistics Authorities (CSA) in collaboration with the World Bank in 2010/11 and 2012/13. The ISA questionnaire of this survey is representative at the national, urban/rural and regional levels and includes household, agriculture, fishery and community questionnaires. It was designed to give information on various dimensions of welfare in Malawi such as household composition and characteristics, health, wages, employment and income sources, as well as other data ranging from consumption and food security to asset ownership. The first wave of the panel includes 3,247 households interviewed from March to November 2010 as part of the larger IHS3. Individuals were tracked over time and once split-off individuals were located, the new households formed since 2010 were included in the second wave. The total number of households interviewed between April and December 2013 was 4,000, 3,104 of which could be traced back to baseline. To avoid a change in the sample composition, we keep only original households[7]. Moreover, given data limitations on

[7] Here, we do not explore the longitudinal dimension of our data for two main reasons. First, a dynamic estimator for QUAIDS has not yet been explored and thus we used repeated time series cross-section for estimation in this paper (Blundell and Robin, 1999). Second, the small T=2 could lead to the incidental parameter truncation of the efficiency frontier estimation especially for True and Random fixed effects (Greene, 2005). Nevertheless, Battese and Coelli (1995) time varying models have been estimated by

dependent and independent variables, our final sample is composed of 2,016 agricultural households, which produce 4,032 observations in the two surveys.

Since the data in our panel are geo-referenced at household and EA-level with latitude and longitude coordinates obtained through hand-held global-positioning system (GPS) devices, we were able to merge the socio-economic data with climate data (our second main source of data) to control for the effects of rainfall variability on household welfare, food security and productivity. Rainfall data are extracted from the Africa Rainfall Climatology version 2 (ARC2) of the National Oceanic and Atmospheric Administration's Climate Prediction Centre (NOAA-CPC) for each dekad (i.e. 10-day intervals) covering the period 1983-2013. ARC2 data are based on the latest estimation techniques on a daily basis and have a spatial resolution of 0.1 degrees (~10km).[8]

4.4.1 QUAIDS data description

Table 1 illustrates descriptive statistics of data utilized in the QUAIDS. It reports the share of consumption utilized in the first and second budgeting stage together with prices, income and proportions of zero expenditures. Moreover, it shows the quantities of inputs purchased through vouchers, their redeeming unit price and the proportion of HHs not receiving the vouchers. In the bottom part of the table, we also reported the HHs' total and agricultural input yearly expenditures. In the first stage, five main categories are identified of which the "A" group (i.e., food and beverages) is the most important one with 65% of total HH expenditure, whereas expenditure on the aggregate agricultural input (group "E") represents only 1.8% of total HH expenditure. The vector of prices for the first stage consists of local prices of the sub-items in each group weighting them with the expenditure shares of the individual item within the group (as suggested in Lewbel, 1989)[9].

In the second stage, we identified five commercial agricultural inputs. What we can see from Table 1 is that the largest share of expenditure is devoted to commercial urea followed by commercial basal with 26.2 and 24.7% of the total agricultural inputs expenditure, respectively. These inputs are also the most broadly utilized as expressed by the low share of households that do not consume them. We notice a high proportion of households with zero expenditure on the other fertilizers and on maize and other seeds, which are usually recycled from the previous season. However, the zero expenditure on commercial inputs could also be driven by owning a voucher. The items subsidised through FISP vouchers are, in fact, perfect substitutes for most of the commercial fertilizers. This has a twofold implication. First, as already assessed in Ricker-Gilbert et al. (2011), when the government and the private sectors act in markets that could be perceived as parallel, consumers may perceive the inputs as substitutes at differentiated prices. When this happens, subsidy-driven public retailers crowd out the demand for commercial inputs. Particularly, if vouchers are also distributed to non-cash constrained farmers, then part of their expenditure on commercial input will certainly be reduced. Second, this competition between inputs allows us to directly observe and estimate the quota elasticities with the aim of verifying the potential demand variation for commercial inputs by farmers under hypothetical new targeting criteria.

showing quite consistent results with the cross-section models. These are available upon request from the authors.

[8] Average of a 10 km radius buffer of the dekadal sum of daily values per enumeration area centroid. For more details on ARC2 algorithms, see: http://www.cpc.ncep.noaa.gov/products/fews/AFR_CLIM/AMS_ARC2a.pdf

[9] The weighting is done with the Laspeyres index to account for spatial variability and adjusted to inflation (Deaton, 1988).

Prices in the second stage are identified through the local market unitary values expressed in MWK/kg according to farmers' self-reported payments and real quantities obtained. The setting of prices for the subsidized inputs deserves careful discussion. Although the redeeming price should be constant across the country, geographical differences are observable even if in many cases, we observe a zero price for redeeming a coupon. There are also 4% of farmers who do not redeem the coupons because they are severely cash constrained. Moreover, a number of farmers declared that they had redeemed more than the threshold level imposed by the government and to this must be added farmers who reported the payment of bribes or the receiving of quantities of inputs that was lower than what they were entitled to, altering the effective redeeming price.

Table[10] 1 Demand system descriptive statistics: Expenditure shares, Prices

Code	Description	Expenditure Share Mean	Expenditure Share (SD)	Price Mean	Price (SD)	Zero expenditure (%)
First stage				Aggregate index (Stone-Lewbel)		
A	Food & beverage	0.654	(0.131)	241.022	(28.441)	-
B	Housing and furnishing	0.192	(0.100)	490.687	(99.418)	-
C	Clothes, transport, education and health	0.096	(0.091)	437.436	(67.022)	-
D	Miscellaneous	0.037	(0.027)	395.199	(56.325)	-
E	Agricultural inputs[11]	0.018	(0.029)	294.664	(107.706)	-
Second stage						
- Commercial				MWK/kg		
W1	Maize seeds	0.077	(0.229)	107.68	(123.81)	0.822
W2	Basal fertilizer	0.247	(0.293)	144.262	(67.71)	0.334
W3	Urea fertilizer	0.262	(0.303)	141.621	(66.56)	0.298
W4	Other fertilizers	0.068	(0.208)	215.390	(113.86)	0.892
W5	Other seeds	0.061	(0.213)	198.746	(135.39)	0.854
- Voucher		Kilograms				
Q1	Maize seed	50.393	(12.739)	20.523	(9.672)	0.776
Q2	Basal fertilizer	50.198	(9.534)	10.107	(5.576)	0.591
Q3	Urea fertilizer	5.577	(2.985)	9.974	(4.336)	0.580
Q4	Other seeds	2.454	(1.934)	8.494	(11.697)	0.922
Total HH expenditure (MKW/year)		441,219	(410,022)			
Total Agricultural Inputs expenditure (MKW/year)		9,064	(24,286)			

1 MWK=0.0029US$ (31/12/2012)

Source: Authors' own elaboration.

4.4.2 Variable construction for stochastic production frontier

Table 2 illustrates descriptive statistics of variables utilized in the stochastic frontier framework. These are classified between agricultural inputs that are utilized to estimate the

[10] All tables and figures in this paper are elaborated by the authors based on their own estimations.
[11] We did not include labour in the agricultural input group since, being principally family labour, there is very limited expenditure on the market.

production function and drivers of inefficiency employed to model the distribution of the one-sided error of the frontier. We used annual maize production as our dependent variable instead of focusing on a multi-crop output for two main reasons. First, maize is the targeted crop in the FISP and has been targeted since the beginning as the strategic crop to subsidize. Second and linked to the first, maize has historically been the most cultivated crop across the country. On average, it covers 57% of cultivated land and is considered the crop of reference for subsistence strategies. Farmers thus orient their farming choices considering maize as the principal staple crop and treat the others as a relay for it (Sileshi et al., 2008). Here we account for the role played by the intercropping and crop diversification following the approach of Chavas and Di Falco (2012) and Di Falco et al. (2010) where mixed crop production is an input in the production function of the main crop. In fact, crop diversification may enhance overall productivity through complementarities, nutrient recycling and the support that it provides to soil biota formation (Altieri, 1999; Barrios, 2007). Moreover, smallholders manage a diversified portfolio of crops as a risk minimization strategy against agricultural shocks (Di Falco et al., 2010; Coromaldi et al., 2015). We thus build an index of diversification, namely the Shannon index, to account for the role of other crops cultivated by farmers[12] on their plots.

The other drivers of inefficiency are identified following the literature[13]. These include household socio-economic and market characteristics (Battese and Coelli, 1995; Seyoum et al., 1998; Coelli and Fleming, 2004), soil attributes and adaptation strategies (Key et al., 2014; Di Falco et al., 2011) and agro-climatic factors (Di Falco and Veronesi, 2013; Byerlee and Heisey, 1996; Nelson et al., 2009; Schenkler and Lobell, 2010). We utilize the standard precipitation index (SPI) as well as surface temperature as our climatic variables. SPI is a widely used indicator (among others Michaelides and Pashiardis, 2008; Whitey and van Kooten, 2011) able to identify variations in precipitation compared with the long-run mean on different time scales[14]. The SPI is based on the probability of recording a given amount of precipitation with such probabilities standardized to produce a value of zero for a median precipitation, whereas the index is negative for drought and positive for wet conditions. This characteristic allows for a straightforward interpretation and full comparability over time and space. In order to compute our climate shock variables, we first calculate the SPI at 12 months for the reference year 2011. The SPI enters the model as a dummy variable which identifies a positive rainfall shock if the SPI assumes a value larger than 1.5 during the growing season.

[12] The Shannon index measures the uncertainty to predict the identity of an individual that is taken randomly from a community (see Di Falco and Perrings, 2005; Coromaldi et al., 2015). Other diversification indices are simple count, Margalef and Berger-Parker (Di Falco et al., 2010).

[13] Other agricultural policy variables (safety net programmes) other than FISP are not included as drivers of inefficiency because they have reduced diffusion and are intended to target poor and marginalized farmers, thereby being endogenous in the farmer's efficiency score (Debela et al., 2015).

[14] The SPI was recommended through the Lincoln Declaration on Drought as the internationally preferred index for meteorological drought (see Hayes *et al*., 2011). To this aim, raw precipitation data are fitted to a gamma or Pearson Type III distribution which is then transformed to a normal distribution (see Guttman, 1999, for further details).

Table 2 Descriptive statistics - stochastic frontier production function

Variable code	Description	Mean	(SD)
Maize	Maize production (kg)	1869.697	(2549.34)
Agricultural inputs (production function)			
Seeds	Maize seeds utilized (kg)	9.108	(44.104)
Organic	Organic fertilizer utilized (kg)	133.189	(499.490)
Urea	Urea utilized (kg)	48.753	(92.893)
Basal	Basal utilized (kg)	71.325	(107.148)
other_fertilizers	Other fertilizers utilized (kg)	34.636	(122.788)
Labour	Labour utilized (men days)	132.677	(160.878)
Area	Area cultivated (hectares)	1.089	(1.066)
Drivers of efficiency (error term)			
A. Socio-economic and market			
head_female	HH female headed (dummy)	0.232	(0.422)
head_age	Age of HH head (years)	43.839	(15.924)
Hhsize	Number of HH members	5.112	(2.322)
educ_15-60	Avg. completed schooling level of HH members between 15-60 years (grade)	5.646	(3.076)
Wealth	Wealth rural index	0.511	(1.763)
Landowner	If farmer owns the cultivated land (%)	0.918	(0.237)
dist_agmrkt	Distance from main agricultural market (km)	21.322	(14.630)
B. Agricultural and soil			
sp_farm	If farmer receives>75% of income from farming (%)	0.291	(0.454)
Antierosion	If farmer applied anti-erosion measures (%)	0.395	(0.489)
Mv	If farmer utilizes modern varieties of maize (%)	0.461	(0.499)
S	Shannon index	2.360	(1.123)
soil_quality			
- poor	If majority of soil is poor quality (%)	0.362	(0.361)
- fair	If majority of soil is fair quality (%)	0.509	(0.494)
- good	If majority of soil is good quality (%)	0.182	(0.444)
soil_type			
- sandy	If majority of soil is sandy (%)	0.154	(0.480)
- mixed	If majority of soil is mixed (%)	0.575	(0.499)
- clay_soil	If majority of soil is clay (%)	0.270	(0.333)
C. *Agro-climatic*			
temperature	Temperature at enumeration area level (°C)	21.188	(1.806)
spi_schock	If farmer experienced a rainfall shock (%)	0.071	(0.258)
Agroecological zone (AEZ)			
- Warm semiarid	Warm semi-arid agroecological zone (%)	0.436	(0.496)
- Warm subhumid	Warm sub-humid agroecological zone (%)	0.316	(0.465)
- Cool semiarid	Cool semi-arid agroecological zone (%)	0.099	(0.299)
- Cool subhumid	Warm semi-humid agroecological zone (%)	0.147	(0.354)

Source: Authors' own elaboration.

5 Results

5.1 Demand system estimations

Table 3 reports the results obtained from the first stage of QUAIDS[15]. It shows expenditure elasticities by the efficiency score quintile and the Marshallian own price elasticity. All the own-price coefficients have negative sign and signal that "food" is the less income responsive category of expenditure, with few differences among quintiles. All the other categories show higher elasticity with the highest range among quintiles observed for the category of "clothes, transport, education and health" and the category of "agricultural inputs".

Table 3 First Stage QUAIDS expenditure elasticities by efficiency quintiles and own price elasticities

Expenditure group	Expenditure elasticity						Own-price elasticity
	Efficiency quintile						
	1	2	3	4	5	Total	
Food and beverage	0.538	0.537	0.536	0.536	0.535	0.536	-0.499
Housing and furnishing	0.985	0.984	0.984	0.984	0.982	0.984	-1.417
Clothes, transport,	0.756	0.779	0.771	0.733	0.703	0.789	-1.169
Education and health							
Miscellaneous	0.824	0.824	0.825	0.825	0.827	0.825	-1.387
Agricultural inputs	0.893	0.895	0.889	0.857	0.853	0.880	-1.031

Source: Authors' own elaboration.

Turning to the analysis of the second stage of QUAIDS, Appendix C shows the results of the probit selection model employed to estimate the conditional probability density function (pdf) and cumulative distribution function (cdf) needed to account for the zero expenditure on commercial inputs and the sample selection occurring between eligible and non-eligible households. The eligibility is thus treated as conditional to the socio-economic characteristics that identify eligible households in the current targeting criteria. The results of QUAIDS are presented in Table 4 where Marshallian expenditure elasticities presented have been calculated at the mean of the efficiency score quintiles.

[15] Results of first stage QUAIDS are available upon request together with cross-price and unconditional elasticities.

Table 4 Second stage QUAIDS Marshallian Expenditure Elasticities

	maize seeds	urea	basal	other fertilizers	other seeds
Expenditure					
eff: 1	0.518	0.743	0.835	1.009	0.902
eff: 2	0.516	0.747	0.85	0.998	0.864
eff: 3	0.549	0.752	0.875	0.982	0.869
eff: 4	0.533	0.75	0.881	0.982	0.828
eff: 5	0.584	0.758	0.91	0.937	0.801
Total	0.54	0.75	0.87	0.982	0.853

Source: Authors' own elaboration.

All the elasticities are positive and consistent with the economic theory. With the exception of maize seeds and urea fertilizer, the other commercial inputs show elasticities close to one. We also note that while for maize seeds, urea and basal, expenditure elasticity increases with the efficiency quintile, the opposite is true for the other fertilizers and seeds.

Table 5 illustrates own and cross price elasticities, together with quota elasticities between commercial and subsidized inputs. As expected, all the own-price elasticities reported on the main diagonal are negative, whereas the cross-price elasticities clearly identify substitute and complementary inputs. Overall, three features emerge from the results presented in Table 5. First, with regard to own price elasticity, we see that maize seeds are perceived as an essential input as shown by a very low value, whereas the other fertilizers are highly price responsive. Furthermore, expenditure on basal decreases more than expenditure on urea as their price increases. Second, there is persistent evidence of high substitutability between the three types of fertilizers and, even at a lower grade, between maize and the other seeds. Third, households recognize maize and the other seeds as being complementary to urea and basal although these characteristics do not hold for other fertilizers.

The lower part of Table 5 illustrates the quota elasticities. At constant redeeming unit price, an increase in the quantity of an input subsidized through vouchers incentivizes households to reduce expenditure on the corresponding commercial input. In fact, we observe a negative quota elasticity for commercial maize seeds, urea and basal. This does not hold for other commercial seeds whose expenditure increases when the HH is eligible for a greater quota of other seeds through the flexi voucher. This outcome could be explained by the fact that incentivizing the adoption of other seeds can stimulate the HH to enlarge their crop portfolio by diversifying with crop varieties in addition to those subsidized with the flexi voucher. Indirect incentives such as diversified seed distribution can indeed reduce the transitional costs of other crop adoption by pushing farmers to enlarge their overall crop diversification (Sunding and Zilberman, 2009).

The complementarity of urea and basal with the maize seeds is also confirmed by these results. In fact, a high subsidized amount of these fertilizers drives an increase in expenditure on commercial maize seeds. The substitution between fertilizers is also persistent whereas an increase in the quota of subsidized maize seeds is associated with an increase in expenditure on other seeds.

Table 5 Second stage QUAIDS: Own, cross price and quota elasticities

	Maize seeds	Urea	Basal	Other fertilizers	Other seeds
Own and Cross Prices					
Maize seeds	-0.207	-1.768	-1.138	0.812	0.433
Urea	-0.232	-0.647	0.826	1.893	-0.891
Basal	-0.187	1.342	-0.944	1.85	-0.982
Other fertilizers	0.251	2.337	-1.226	-1.903	0.639
Other seeds	0.522	-1.618	-0.936	0.758	-0.806
Quota (vouchers)					
Maize seeds	-0.427	0.347	0.284	0.098	-0.537
Urea	0.384	-0.808	-0.601	-1.504	-0.349
Basal	0.207	-0.312	-1.014	-2.173	0.584
Other seeds (flexi)	-0.209	0.199	0.109	0.321	0.389

Source: Authors' own elaboration.

5.2 Efficiency estimation

Table 6 presents the results of the stochastic frontier production function represented by a Cobb-Douglas function and, as an alternative a translog functional form to control for consistency between diverse specifications, both clustered at district level.[16] The upper part of Table 6 presents the elasticities of the production function. In the case of the translog functional form, we report only the interaction terms between inputs that are significant. These add flexibility to the specification of the function and allows verify whether there is an impact on production when the rate of inputs are modified contemporaneously. In both models, all the inputs increase maize production with the exception of organic fertilizers, which are statistically significant only in their quadratic term. The main impact on yield is given by the size of cultivated land, followed by seeds and labour. In the translog specification, decreasing marginal returns are observed on seeds, basal fertilizer and land.

The parameter estimates of the inefficiency drivers are presented in the lower part of Table 6. Results are robust for both the functional forms and confirm expectations. Technical efficiency is positively correlated with household size, higher education level, higher wealth endowment (with the larger marginal effect associated to a middle wealth, with this expressed in tertiles), ownership of the cultivated land, a specialization in agriculture, adoption of modern varieties of maize and application of anti-erosion measures. Moreover, households that cultivate a mixed or clay soil are more efficient than those cultivating sandy soil. In 2013, *ceteris paribus*, the level of efficiency was higher for maize production. On the contrary, lower technical efficiency is associated with households that are female headed,

[16] Following Mundlak, pseudo-fixed effects are obtained by means of plot-varying input rates in the production function. Such an extension allows the existence of plot-varying exogenous unobservable variables such as skills of workers in the single plot or soil characteristics that affect productivity to be exploited (Di Falco and Bulte, 2013). This unobservable heterogeneity bias may not be independently distributed along the explanatory variables and plots, needing correction via Mundlak devices. An *F* test rejects the null hypothesis that the Mundlak coefficients are jointly equal to zero.

distant from the main agricultural markets, work on fair or poor soils and live in sub-humid warm or cool agro-ecological zones with higher surface temperatures.

Table 6 Stochastic production frontier

	Translog		Cobb-Douglas	
	Mean	**(se)**	**Mean**	**(se)**
Frontier				
Seeds	0.267***	(0.063)	0.058**	(0.023)
seeds2	-0.095***	(0.022)		
Organic	0.017	(0.021)	0.015***	(0.006)
organic2	0.007*	(0.004)		
Basal	0.044***	(0.014)	0.035***	(0.007)
basal2	-0.030***	(0.010)		
Urea	0.064**	(0.029)	0.017**	(0.007)
urea2	-0.012	(0.011)		
other_fertilizer	0.101***	(0.034)	0.017**	(0.008)
other_fertilizer2	-0.006	(0.013)		
Labour	0.108**	(0.052)	0.021*	(0.011)
labour2	0.016	(0.012)		
Area	1.307***	(0.178)	1.105***	(0.067)
area2	-0.249***	(0.124)		
seeds*area	0.363***	(0.087)		
organic*area	0.080**	(0.035)		
urea*other_fertilizer	-0.009*	(0.005)		
other_fertilizer*labour	-0.024**	(0.010)		
labour*area	0.144***	(0.050)		
plot fixed effects	yes		Yes	
_cons	5.461***	(0.167)	6.192***	(0.087)
Mu				
head_female	0.051*	(0.030)	0.062*	(0.035)
head_age	-0.030	(0.045)	0.004	(0.057)
Hhsize	-0.111**	(0.043)	-0.144***	(0.054)
educ_15_60	-0.070***	(0.022)	-0.074***	(0.027)
wealth: 2	-0.199***	(0.047)	-0.199***	(0.055)
wealth: 3	-0.055*	(0.033)	-0.050	(0.041)
Landowner	-0.212**	(0.124)	-0.358**	(0.160)
dist_agmrkt	0.041*	(0.024)	0.028	(0.033)
sp_farm	-0.112***	(0.033)	-0.135***	(0.043)
Antierosion	-0.085***	(0.030)	-0.107***	(0.037)
Mv	-0.328***	(0.038)	-0.380***	(0.047)
S	1.039**	(0.510)	1.621***	(0.686)
S2	-0.887***	(0.159)	-0.628	(0.452)
Temperature	1.571***	(0.320)	2.206***	(0.412)
spi_shock_tot	-0.095*	(0.059)	-0.106	(0.097)
soil_quality: fair	0.011	(0.031)	0.025	(0.039)
soil_quality: poor	0.085**	(0.041)	0.110**	(0.051)
soil_type: mixed	-0.135***	(0.044)	-0.139***	(0.053)
soil_type: clay	-0.196***	(0.049)	-0.236***	(0.062)
AEZ: warm-subhumid	0.368***	(0.043)	0.466***	(0.056)
AEZ: cool-semiarid	0.088	(0.069)	0.126	(0.094)
AEZ: cool-subhumid	0.129*	(0.068)	0.206**	(0.090)
year_2013	-0.104***	(0.029)	-0.159***	(0.025)
_cons	201.329***	(57.097)	307.193***	(49.337)
Usigma				
S	-1.329***	(0.242)	-1.309***	(0.228)
_cons	-0.222	(0.277)	0.177	(0.292)
Vsigma				
_cons	-1.659***	(0.086)	-1.665***	(0.070)
N	4032		4032	
Log pseudolikelihood	-3438.132		-3595.304	

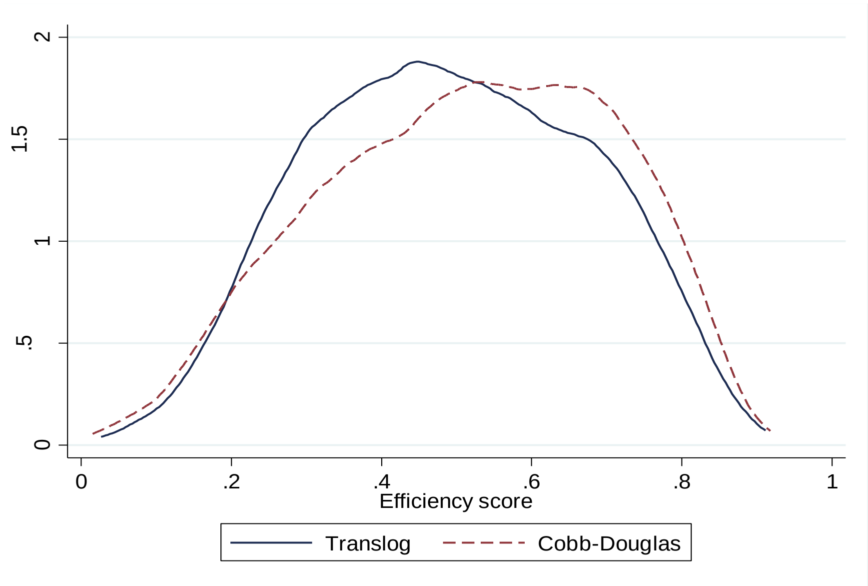
Note: $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$; LR test of functional form = 314.35, Prob >chi2 =0.000; F-test on pseudo-fixed effects: Translog=52.81, Prob>chi2=0.000, Cobb-Douglas=62.04, Prob>chi2=0.000. District clustered standard errors in parenthesis.

Source: Authors' own elaboration

The efficiency reduction is also driven by crop diversification, though, with a decreasing rate as shown by the coefficient of its quadratic term. Since diversification is a risk minimizing strategy in which a premium to the risk is paid by risk adverse households, higher diversification tends to have a negative impact on efficiency. However, crop diversification can reduce the variability of production capacity (Chavas and Di Falco, 2011; Di Falco and Perrings. 2005). We tested this hypothesis by modelling the variance of the one-sided error term as dependent and the Shannon diversification index as an independent variable. We obtain a negative and significant coefficient for diversification confirming the positive role of crop diversification in reducing the overall variability of production. It is also worth noting that a positive rainfall shock, captured by the SPI dummy, is a factor that positively influences efficiency. In a mainly rainfed agriculture, this is not surprising even if this result may be sensitive to the threshold utilized for defining the shock, here given by a SPI>1.5 standard deviations.

Building on these results, we illustrate an ideal profile of efficient farmers. This profile should drive a review of FISP targeting criteria because it is compatible with the constraint faced by policy makers observe the drivers of efficiency but not the score of efficiency. Figure 1 shows the probability density function of this score (or kernel density) which can assume values comprised between 0 and 1 with households far from 1 being more technically inefficient than those closer to the frontier. Our estimates produce average efficiency scores ranging from 0.49 to 0.51 for the translog and Cobb-Douglas functional forms, respectively.

Figure 1 Density of efficiency score



Source: Authors' own elaboration.

In the lower part of Table 7, we report the efficiency scores at national level by also illustrating their variation according to three exogenous drivers of inefficiency, namely wealth tertiles, agro-ecological zones and the survey year. It is quite interesting to see that efficiency score is the highest in the medium wealth tertiles and for household s residing in warm-semiarid agro-ecological zones.

Table 7 Mean Efficiency scores (JLMS estimator)

	Translog		Cobb-Douglas	
	Mean	**(sd)**	**mean**	**(sd)**
wealth: 1	0.466	(0.180)	0.488	(0.187)
wealth: 2	0.538	(0.175)	0.558	(0.186)
wealth: 3	0.484	(0.178)	0.511	(0.189)
AEZ: warm-semiarid	0.548	(0.165)	0.582	(0.172)
AEZ: warm-subhumid	0.394	(0.168)	0.412	(0.179)
AEZ: cool- semiarid	0.545	(0.165)	0.567	(0.172)
AEZ: cool- subhumid	0.522	(0.173)	0.547	(0.180)
year: 2011	0.461	(0.187)	0.472	(0.195)
year: 2013	0.521	(0.169)	0.557	(0.174)
Total national	0.491	(0.180)	0.515	(0.190)

Source: Authors' own elaboration.

With this set of results, it is interesting to compare how the distribution of vouchers has occurred in the current FISP targeting, compared with the estimated efficiency scores. Table 8 shows the cumulative proportion of vouchers according to five quintiles of the efficiency scores obtained from the translog model[17]. On average, all the efficiency classes received a similar proportion of the total vouchers distributed across the country, with a peak observed at the second quintile in both survey years and the lowest share of vouchers attributed to the less efficient farmers. Overall, the three bottom quintiles of efficiency received around 58% and 59% of the total vouchers calculated for 2010 and 2013, respectively.

Table 8 Proportion of vouchers, by efficiency quintiles

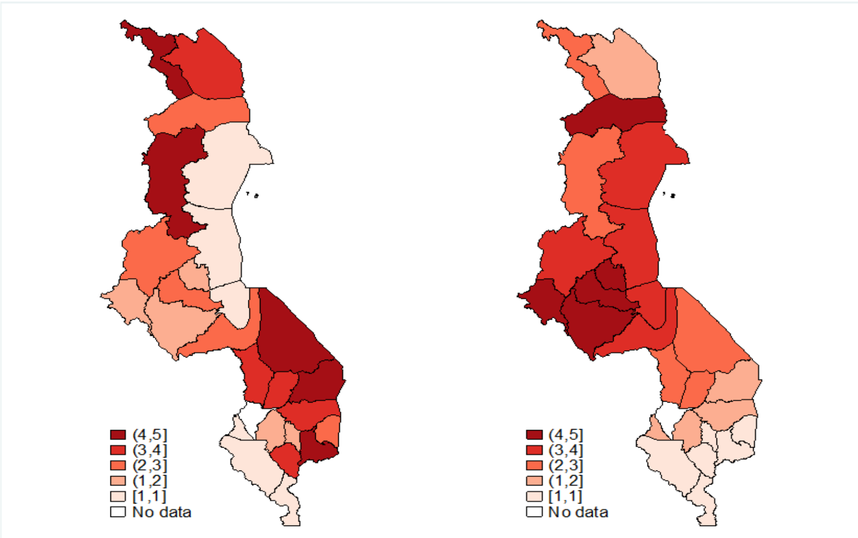
	2011		2013	
	(%)	Cumul	(%)	Cumul
Efficiency:1	0.181	-	0.175	-
Efficiency:2	0.211	0.382	0.218	0.392
Efficiency:3	0.203	0.585	0.201	0.593
Efficiency:4	0.200	0.795	0.193	0.786
Efficiency:5	0.204	1	0.213	1

Source: Authors' own elaboration.

[17] According to the LR test and joint significance test on parameter significance, we accept the significance of the unrestricted model. Thus, from now on and for policy simulation, we utilize the elasticities of the translog functional form.

Figure 2 replicates the previous analysis but focuses on the district level and shows the between years mean. In particular, the first map (a) reports the quintiles of the proportions of total vouchers received by the districts whereas the second map (b) shows the average efficiency score, grouped by quintiles, observed in a district. Districts in the central region received a low share of total vouchers despite being more efficient than the mean national level. On the contrary, districts in the south-east, even if showing low average efficiency performance, are in the highest quintile of share of vouchers obtained.

Figure 2 Quintiles of share of vouchers received on total distributed and quintiles of the efficiency score, at district level.



a) Share of vouchers b) Efficiency scores

Source: Authors' own elaboration.

5.3 Policy simulation

To analyse the overall impact of modified targeting criteria, we use elasticities from the QUAIDS and the stochastic frontier as described in Section 4.1, 4.2 and the Appendix A. The effects of changing targeting based on efficiency criteria on food expenditure and maize production are evaluated on three categories of households. The first category includes what are considered inefficient households that lose their eligibility for the FISP and are in the lowest wealth class, which are regarded here as "ultra-poor losers". The second group includes all other households losing, which are in the lowest three quintiles of inefficiency but are not classified as ultra-poor. The third set of households includes the winners who belong to the first two quintiles of efficiency scores and are potentially eligible for the FISP.

Moreover, we conducted the simulation on four different scenarios constructed as follows:

- Scenario 1: the vouchers are shifted from "losers" to "winners" with the quintiles of efficiency evaluated on a national scale level;
- Scenario 2: the same as Scenario 1 but with the shifting of vouchers based on efficiency quintiles calculated within a district with the current spatial distribution of vouchers kept constant;

- Scenario 3: the quintiles at national level are used as in the first scenario, but now we include a lump-sum compensation for the “ultra-poor losers” group to reduce distributional concerns caused by the new targeting criteria. This scenario allows for an increase in the government FISP budget to guarantee both a constant value of total voucher distributed and compensation for the ultra-poor category that is equal to the market value of the vouchers for which they are not eligible;
- Scenario 4: the same as Scenario 3 but with budget neutrality and, as such, both individual lump-sum compensation and the total value of vouchers distributed to winners are halved[18].

Policy scenarios are evaluated assuming that all other factors are constant which makes these simulations suitable for investigating the marginal impact of varying the targeting criteria or providing compensation for the ultra-poor. Results of policy simulation are presented in Table 9. We observe that all the scenarios produce positive results with regard to the net impact on food expenditure. As expected, the best outcome corresponds to Scenario 3 where the increase in the food expenditure is equal to 0.81%. Here, the higher national average impact is driven by the variation in expenditure of the ultra-poor who benefit from the extra-income received through lump-sum compensation. However, this scenario is not budget-neutral, so the welfare increase associated with this scenario comes at an additional cost to the government.

The losers also benefit from zero expenditure on vouchers (being no longer eligible) which is less than proportionally substituted by the expenditure on commercial agricultural inputs. Such an interpretation is strengthened by a reduction in ultra-poor maize production equal to -0.3%. Nevertheless, such a loss is lower than the one observed in all the other scenarios because the high extra income from government compensation is also partly devoted to agricultural input expenditure. This pushes the ultra-poor to substitute subsidized with commercial inputs at a higher rate than in compensation scenarios.

Similar interpretations also hold for Scenario 4, even though there are lower benefits for the ultra-poor, given the reduction in the amount of compensation. Nevertheless, we note that the net impact on maize production is lower than in Scenario 1 because of the amount of vouchers distributed has been halved which constrains the number of winners. Relative to Scenario 3, the net impact has not been halved because the restricted group of winners includes households with the highest rank of the efficiency score that, on average, produce higher maize performances than the enlarged group of winners (those in Scenarios 1 and 3).

Scenario 2, though positive with respect to the baseline, produces the worst performance, because vouchers are not distributed according to “pure” efficiency criteria at national scale, but by preserving the proportion of vouchers distributed between districts. In this case, districts that are structurally not efficient continue to receive more vouchers than they would on a pure efficiency basis, producing the lowest net national impact for both food expenditure and maize production. However, from a political economy perspective, this scenario is also the most viable since it is least disruptive of the existing allocation of funds to political districts.

[18] The impact of simulating a distribution of the budget between cash compensation and the vouchers that is different from the half is midway between the results of Scenarios 1 and 4.

Table 9 Policy simulation

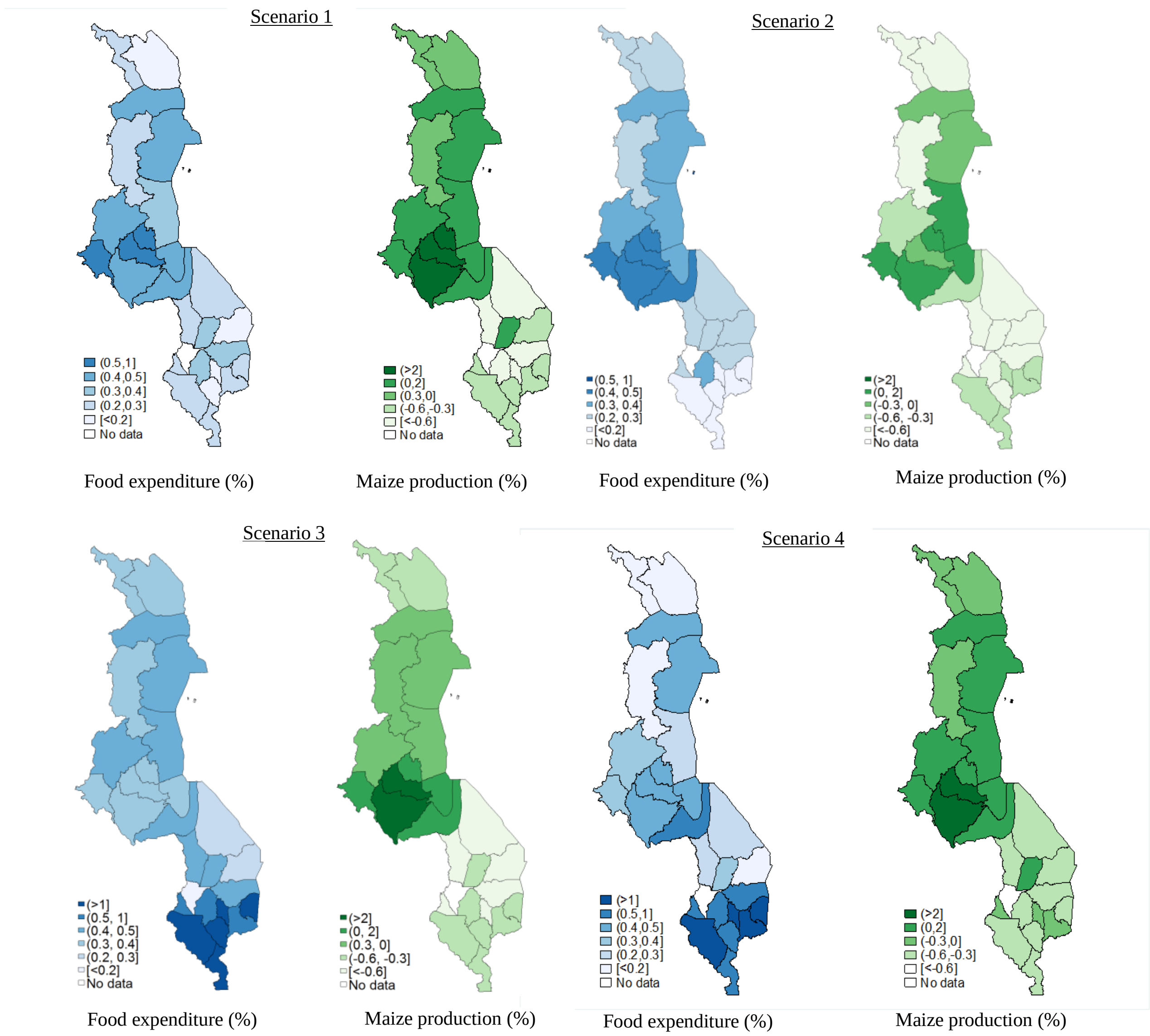
	Food expenditure (% variation)				Maize production (% variation)			
	ultra-poor	other losers	winners	net impact	ultra-poor	other losers	winners	net impact
Scenario 1: vouchers to efficient HHs (at national level)	0.211	0.289	0.501	0.305	-0.525	-0.727	2.152	0.904
Scenario 2: vouchers to efficient HHs (at district level)	0.189	0.254	0.415	0.275	-0.547	-0.785	1.158	0.211
Scenario 3: same as 1, compensating ultra-poor	1.774	0.289	0.501	0.812	-0.310	-0.727	2.152	1.314
Scenario 4*: same* as 3*,* but budget neutral	1.008	0.289	0.453	0.502	-0.391	-0.727	1.810	0.802

Source: Authors' own elaboration.

While Scenario 2 produce the lowest result, Scenario 3 is the best option. However, the latter is highly expensive for the government and, thus, likely to be unfeasible. At a constant FISP budget, Scenario 1 and 4, produce contrasting results. Scenario 1 provides a better outcome in terms of maize production whereas Scenario 2 is preferred in terms of food expenditure and equity of the programme. All the scenarios are compared at district level in Figure 3.

In particular, when looking at the food expenditure variation, with regard to Scenario 1, the southern districts are the main beneficiaries from applying Scenario 4 because of a high share of ultra-poor losers. On the contrary, central districts, which are among the more efficient (see Figure 2), suffer slightly from a reduction in the amount of vouchers distributed in Scenario 4 which excludes several efficient farmers from benefiting from the extra income released by purchasing inputs at a subsidized price. The maize production figure shows little differences between scenarios, with the exception of some districts in the south that gain from Scenario 4, given the compensation and the reduction in the use of agricultural inputs that is lower than those for Scenario 1.

Figure 3 Percentage average variation of food expenditure and maize production at district level



Source: Authors' own elaboration.

6 Conclusions and policy implications

The Malawian FISP has been, since its inception in 2005, one of the biggest agricultural input subsidy programs in developing countries. Despite national statistics showing an increase in productivity and a reduction in undernourishment, an ongoing debate at national and international level seeks to understand whether the full potential of the programme is currently exploited or whether specific improvements could be explored, especially in view of a high share of the public budget devoted to it. In particular, the government and previous literature suggest that the overall impact of FISP could be strengthened by targeting farmers that could have the higher returns from the subsidized agricultural impacts instead of targeting vulnerable farmers *per se*.

In this paper, we have simulated the impact of varying eligibility criteria on food expenditure and maize production by targeting efficient farmers and, when necessary, compensating the ultra-poor farmers who emerge as losers. Our results highlight that efficient farmers are landowners who specialize in agriculture, with middle rural wealth endowment and investment in anti-erosion measures on their plots. It is also worth stressing that households living in semi-arid agro-ecological zones, both warm and cool, are on average more efficient than households living in sub-humid zones, thus providing useful insights into spatially identifying eligible farmers. Consequently, in the context of Malawi, districts located in the centre are advantaged in terms of production capacity, whereas those in the south are structurally among the least efficient. Moreover, farmers with a high level of crop diversification tend to have less efficiency but gain in terms of reduced variability of the outcome. Results also show that farmer demands for non-maize commercial seeds rise as the subsidies on other seeds increase and fall with the increasing distribution of maize seed vouchers. These findings suggest that an increase in maize seed subsidies seems to incentivize mono cropping, which can benefit well-endowed farmers who do not face climatic soil quality constraints. However, there is room for increasing the amount of vouchers for other seeds by targeting vulnerable inefficient farmers, especially in structurally inefficient zones for maize production.

Overall, an alternative targeting policy consisting of distributing vouchers to more efficient farmers is found to produce positive variation at national level although this is limited. Food expenditure variation ranges from 0.27% to 0.8% and maize production from 0.2% to 1.3%. Nevertheless, many ultra-poor farmers lose their eligibility. In this respect, we argue that these farmers should be compensated to preserve the equity of the policy. This compensation, set to the value of vouchers received in the current FISP, would produce better outcomes on both our measures. However, this policy scheme is not budget neutral and may not be feasible given the current large share of government budgets on the FISP. Alternatively, budget-neutral correction mechanisms with reduced compensation for ultra-poor farmers losing eligibility would still produce positive results on food expenditure, but would reduce the gains in national maize productivity resulting from a reduction in distributed vouchers. It is important to point out that this result largely depends on the costs of fertilizers sustained by the government, which we assume to be constant. If the government were to reduce these costs, a budget-neutral FISP may still result in outcomes that, in terms of food expenditure, are similar to those of the scenario with reduced compensation or the scenario without budget constraints.

Although cash compensation benefits ultra-poor households in terms of food expenditure, with increases between 1% and 1.7%, varying the targeting criteria along the lines evaluated here seems to damage the ultra-poor in terms of maize production, with an upper bound estimated reduction of 0.5%. The government could therefore enhance the budget devoted to other programmes, such as those for improved agricultural practices, by targeting all the losers and those who are inefficient in maize production. Alternatively, or in combination with the latter, the government could invest in infrastructural policies to incentivize non-farming labour in inefficient agricultural areas. A further policy implication of our results is that, in order to maximize the net impact of the FISP, the allocation procedures should be centralized. Indeed, the identification of eligible households should be based on their aforementioned characteristics at national level and vouchers should be oriented towards zones and districts that are structurally efficient.

Our findings, overall, suggest that reviewing the FISP targeting criteria can improve the cost-effectiveness of the programme, even if on a limited scale. At the same time, some concerns arise regarding the equity of the new targeting. Room for ameliorating the subsidy policy still exists and more research is needed to compare the impact of alternative scenarios by evaluating, for instance, the impact of switching from a voucher system, which has been shown to produce confusing allocation procedures, to a universal subsidy system combined with safety net programmes for severely cash-constrained farmers.

References

Aigner, D., Lovell, C. K., & Schmidt, P. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21-37.

Altieri, M. A. 1999. The ecological role of biodiversity in agroecosystems. *Agriculture, Ecosystems & Environment*, *74*(1), 19-31.

Arndt, C., Pauw, K., & Thurlow, J. 2016. The Economy-wide Impacts and Risks of Malawi's Farm Input Subsidy Program. *American Journal of Agricultural Economics*, *98*(3), 962-980.

Asche, F., & Wessells, C. R. 1997. On price indices in the almost ideal demand system. *American Journal of Agricultural Economics*, 1182-1185.

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. 2012. Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, *37*(3), 283-295.

Attanasio, O., Di Maro, V., Lechene, V., & Phillips, D. 2013. Welfare consequences of food prices increases: Evidence from rural Mexico. *Journal of Development Economics*, *104*, 136-151.

Banks, J., Blundell, R., & Lewbel, A. 1997. Quadratic Engel curves and consumer demand. *Review of Economics and Statistics*, *79*(4), 527-539.

Bardhan, P. 1996. Efficiency, equity and poverty alleviation: Policy issues in less developed countries. *The Economic Journal*, 1344-1356.

Barrios, E. 2007. Soil biota, ecosystem services and land productivity. *Ecological economics*, *64*(2), 269-285.

Battese, G. E., & Coelli, T. J. 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical economics*, *20*(2), 325-332.

Bellon, M. R. 2004. Conceptualizing interventions to support on-farm genetic resource conservation. *World Development*, *32*(1), 159-172.

Blundell, R., & Robin, J. M. 1999. Estimation in large and disaggregated demand systems: an estimator for conditionally linear systems. *Journal of Applied Econometrics*, *14*(3), 209-232.

Bravo-Ureta, B. E. 2014. Stochastic frontiers, productivity effects and development projects. *Economics and Business Letters*, *3*(1), 51-58.

Cappellari, L., & Jenkins, S. P. 2003. Multivariate probit regression using simulated maximum likelihood. *The Stata Journal*, *3*(3), 278-294.

Chibwana, C., Fisher, M., & Shively, G. 2012. Cropland allocation effects of agricultural input subsidies in Malawi. *World Development*, *40*(1), 124-133.

Coelli, T., & Fleming, E. 2004. Diversification economies and specialisation efficiencies in a mixed food and coffee smallholder farming system in Papua New Guinea. *Agricultural Economics*, *31*(2-3), 229-239.

Coelli, T., Rahman, S., & Thirtle, C. 2003. A stochastic frontier approach to total factor productivity measurement in Bangladesh crop agriculture, 1961–92. *Journal of International Development*, *15*(3), 321-333.

Collier, P. & Dercon, S. 2014. African Agriculture in 50Years: Smallholders in a Rapidly Changing World?. *World Development*, *63*, 92-101.

Conley, T. G., & Udry, C. R. 2010. Learning about a new technology: Pineapple in Ghana. *The American Economic Review*, 35-69.

Coromaldi M., Pallante G., Savastano, S. 2015. Adoption of modern varieties, farmers' welfare and crop biodiversity: Evidence from Uganda. *Ecological Economics*, 119, 346-358.

Crawford, E., Kelly, V., Jayne, T. S., & Howard, J. 2003. Input use and market development in Sub-Saharan Africa: an overview. *Food Policy*, *28*(4), 277-292.

De Janvry, A., & Sadoulet, E. 2002. World poverty and the role of agricultural technology: direct and indirect effects. *Journal of Development Studies*, *38*(4), 1-26.

Deaton, A. 1988. Quality, quantity, and spatial variation of price. *The American Economic Review*, 418-430.

Deaton, A., & Muellbauer, J. 1980. An almost ideal demand system. *The American economic review*, 312-326.

Dercon, S., & Gollin, D. 2014. Agriculture in African development: theories and strategies. *Annu. Rev. Resour. Econ.*, *6*(1), 471-492.

Di Falco, S., & Perrings, C. 2005. Crop biodiversity, risk management and the implications of agricultural assistance. *Ecological economics*, *55*(4), 459-466.

Di Falco, S., Bezabih, M., & Yesuf, M. 2010. Seeds for livelihood: Crop biodiversity and food production in Ethiopia. *Ecological Economics*, *69*(8), 1695-1702.

Di Falco, S., Veronesi, M., & Yesuf, M. 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829-846.

Dorward, A. 2006. Markets and pro-poor agricultural growth: insights from livelihood and informal rural economy models in Malawi. *Agricultural Economics*, *35*(2), 157-169.

Dorward, A. R. and Chirwa, E. W. 2015, Crowding out, diversion, and benefit/cost assessments in fertilizer subsidy programs in sub-Saharan Africa: a comment on Jayne, T.S., Mather, D., Mason, N.,

Dorward, A., & Chirwa, E. 2011. The Malawi agricultural input subsidy programme: 2005/06 to 2008/09. *International journal of agricultural sustainability*, *9*(1), 232-247.

Druilhe, Z. and Barreiro-Hurle, J. 2012. Fertilizer subsidies in sub-Saharan Africa. FAO ESA working paper No 12-04, Rome Italy.

Dyer, G. A., Boucher, S., & Taylor, J. E. 2006. Subsistence response to market shocks. *American Journal of Agricultural Economics*, *88*(2), 279-291.

Dzanku, F. M., Jirström, M., & Marstorp, H. 2015. Yield gap-based poverty gaps in rural Sub-Saharan Africa. *World Development*, *67*, 336-362.

Ecker, O., & Qaim, M. 2011. Analyzing nutritional impacts of policies: an empirical study for Malawi. *World Development*, *39*(3), 412-428.

Edgerton, D. L. 1997. Weak separability and the estimation of elasticities in multistage demand systems. *American Journal of Agricultural Economics*, *79*(1), 62-79.

Ellis, F., & Maliro, D. 2013. Fertiliser subsidies and social cash transfers as complementary or competing instruments for reducing vulnerability to hunger: The case of Malawi. *Development Policy Review*, *31*(5), 575-596.

Filippini, M., & Hunt, L. C. 2012. US residential energy demand and energy efficiency: A stochastic demand frontier approach. *Energy Economics*, *34*(5), 1484-1491.

Fisher, M., & Kandiwa, V. 2014. Can agricultural input subsidies reduce the gender gap in modern maize adoption? Evidence from Malawi. *Food Policy*, *45*, 101-111.

Gao, X. M., Wailes, E. J., & Cramer, G. L. 1996. A two-stage rural HH demand analysis: Microdata evidence from Jiangsu Province, China. *American Journal of Agricultural Economics*, *78*(3), 604-613.

Gómez, M. I., Barrett, C. B., Raney, T., Pinstrup-Andersen, P., Meerman, J., Croppenstedt, A., ... & Thompson, B. 2013. Post-green revolution food systems and the triple burden of malnutrition. *Food Policy*, *42*, 129-138.

Greene, W. 2005. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, *126*(2), 269-303.

Hadri, K. 2000. Testing for stationarity in heterogeneous panel data. *The Econometrics Journal*, 148-161.

Heien, D., & Wesseils, C. R. 1990. Demand systems estimation with microdata: a censored regression approach. *Journal of Business & Economic Statistics*, *8*(3), 365-371.

Holden, S. T., & Lunduka, R. W. 2014. Input subsidies, cash constraints, and timing of input supply. *American Journal of Agricultural Economics*, *96*(1), 290-307.

Holden, S., Shiferaw, B., & Pender, J. 2004. Non-farm income, household welfare, and sustainable land management in a less-favoured area in the Ethiopian highlands. *Food Policy*, *29*(4), 369-392.

Jayne, T. S., & Rashid, S. 2013. Input subsidy programs in sub-Saharan Africa: a synthesis of recent evidence. *Agricultural economics*, *44*(6), 547-562.

Jayne, T.S., Mather, D., Mason, N. and Ricker-Gilbert, J. 2013. How do fertilizer subsidy programs affect total fertilizer use in sub-Saharan Africa? Crowding out, diversion, and benefit/cost assessments. Agric. Econ. 44(6), 687–703.

Jondrow, J., Materov, I., Lovell, K., Schmidt, P. 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics* 19 (2/3), 233–238.

Jones, A. D., Shrinivas, A., & Bezner-Kerr, R. 2014. Farm production diversity is associated with greater household dietary diversity in Malawi: findings from nationally representative data. *Food Policy*, *46*, 1-12.

Kelly, V., Adesina, A. A., & Gordon, A. 2003. Expanding access to agricultural inputs in Africa: a review of recent market development experience. *Food Policy*, *28*(4), 379-404.7

Key, N., & Sneeringer, S. 2014. Potential Effects of Climate Change on the Productivity of US Dairies. *American Journal of Agricultural Economics*, *96*(4), 1136-1156.

Kijima, Y., Otsuka, K., & Sserunkuuma, D. 2011. An inquiry into constraints on a green revolution in Sub-Saharan Africa: the case of NERICA rice in Uganda. *World Development*, *39*(1), 77-86.

Kumbhakar S.C., Wang H.J. & Alan, P. 2015. A practitioner's guide to stochastic frontier analysis using Stata. Cambridge University Press.

Kumbhakar, S.C. 1990. Production frontiers, panel data, and time-varying technical inefficiency. *Journal of econometrics*, *46*(1), 201-211.

Lancaster, K. J. 1966. A new approach to consumer theory. *The journal of political economy*, 132-157.

Lecocq, S., & Robin, J. M. 2015. Estimating almost-ideal demand systems with endogenous regressors. *Stata Journal*, *15*(2), 554-573.

Liverpool, L. S. O., & Winter-Nelson, A. 2010. Poverty status and the impact of formal credit on technology use and wellbeing among Ethiopian smallholders. *World Development*, *38*(4), 541-554.

Lunduka, R., Ricker-Gilbert, J., & Fisher, M. 2013. What are the farm-level impacts of Malawi's farm input subsidy program? A critical review. *Agricultural Economics*, *44*(6), 563-579.

Lyssiotou, P., Pashardes, P., & Stengos, T. 1999. Testing the rank of Engel curves with endogenous expenditure. *Economics Letters*, *64*(1), 61-65.

Michaelides, S., & Pashiardis, S. 2008. Monitoring drought in Cyprus during the 2007-2008 hydrometeorological year by using the standardized precipitation index (SPI). *European Water*, *23*(24), 123-131.

Miller, C. M., Tsoka, M., & Reichert, K. 2011. The impact of the Social Cash Transfer Scheme on food security in Malawi. *Food policy*, *36*(2), 230-238.

Minviel, J. J., & Latruffe, L. 2017. Effect of public subsidies on farm technical efficiency: a meta-analysis of empirical results. *Applied Economics*, *49*(2), 213-226.

Mottaleb, K. A., Mohanty, S., & Mishra, A. K. 2015. Intra-HH Resource Allocation under Negative Income Shock: A Natural Experiment. *World Development*, *66*, 557-571.

Otsuka, K., & Larson, D. F. 2012. *An African Green Revolution: Finding ways to boost productivity on small farms*. Springer Science & Business Media.

Pitt, M. M., & Lee, L. F. 1981. The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of development economics*, *9*(1), 43-64.

Platoni, S., Sckokai, P., & Moro, D. 2012. Panel data estimation techniques and farm-level data models. *American Journal of Agricultural Economics*, aas072.

Poi, B. P. 2012. Easy demand-system estimation with quaids. *Stata Journal*, *12*(3), 433.

Reardon, T., Taylor, J. E., Stamoulis, K., Lanjouw, P., & Balisacan, A. 2000. Effects of non-farm employment on rural income inequality in developing countries: an investment perspective. *Journal of agricultural economics*, *51*(2), 266-288.

Rosegrant, M. W., Kasryno, F., & Perez, N. D. 1998. Output response to prices and public investment in agriculture: Indonesian food crops. *Journal of Development Economics*, *55*(2), 333-352.

Ryan, D. L., & Wales, T. J. 1999. Flexible and semiflexible consumer demands with quadratic Engel curves. *Review of Economics and Statistics*, *81*(2), 277-287.

Sabates-Wheeler, R., & Devereux, S. 2010. Cash transfers and high food prices: explaining outcomes on Ethiopia's productive safety net programme. *Food Policy*, *35*(4), 274-285.

Schmidt, P., & Sickles, R. C. 1984. Production frontiers and panel data. *Journal of Business & Economic Statistics*, *2*(4), 367-374.

Seyoum, E. T., Battese, G. E., & Fleming, E. M. 1998. Technical efficiency and productivity of maize producers in eastern Ethiopia: a study of farmers within and outside the Sasakawa-Global 2000 project. *Agricultural economics*, *19*(3), 341-348.

Sherlund, S. M., Barrett, C. B., & Adesina, A. A. 2002. Smallholder technical efficiency controlling for environmental production conditions. *Journal of development economics*, *69*(1), 85-101.

Shonkwiler and Yen reconsidered. *Applied Economics*, *37*(4), 367-374.

Shonkwiler, J. S., & Yen, S. T. 1999. Two-step estimation of a censored system of equations. *American Journal of Agricultural Economics*, *81*(4), 972-982.

Sileshi, G., Akinnifesi, F. K., Ajayi, O. C., & Place, F. 2008. Meta-analysis of maize yield response to woody and herbaceous legumes in sub-Saharan Africa. *Plant and soil*, *307*(1-2), 1-19.

Suri, T. 2011. Selection and comparative advantage in technology adoption. *Econometrica*, *79*(1), 159-209.

Taylor, T. G., & Shonkwiler, J. S. 1986. Alternative stochastic specifications of the frontier production function in the analysis of agricultural credit programs and technical efficiency. *Journal of development economics*, *21*(1), 149-160.

Tittonell, P., & Giller, K. E. 2013. When yield gaps are poverty traps: the paradigm of ecological intensification in African smallholder agriculture. *Field Crops Research*, *143*, 76-90.

Wang, H. J. 2002. Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. *Journal of Productivity Analysis*, *18*(3), 241-253.

Wanzala-Mlobela, M., Fuentes, P. & Mkumbwa, S. 2011. Best practices and policy options for implementing fertilizer subsidy programs successfully in Sub-Saharan Africa. NEPAD Policy Study, Policy Alignment and Programme Development Directorate, NPCA, December. (mimeo)

Withey, P., & van Kooten, G. C. 2011. The effect of climate change on optimal wetlands and waterfowl management in Western Canada. *Ecological Economics*, *70*(4), 798-805.

Yen, S. T. 2005. A multivariate sample-selection model: estimating cigarette and alcohol demands with zero observations. *American Journal of Agricultural Economics*, *87*(2), 453-466.

Appendix A

A.1 QUAIDS

In the QUAIDS, the consumer indirect utility function (*V*) of each household [19] is represented as follow:

$$lnV = \left\{ \left[\frac{\ln m - ln\, a(p)}{b(p)} \right]^{-1} + \lambda(p) \right\}^{-1} \tag{1}$$

where m stands for the total expenditure on a consumption group and p is a vector of prices associated with the items ι included in the group aggregator. The functions $ln\, a(p)$ and $b(p)$ represents the translog and the Cobb-Douglas price aggregator functions and can be respectively represented in the form:

$$ln\, a(p) = \alpha_0 + \sum_{\iota=1}^{n} \alpha_\iota lnp_\iota + \frac{1}{2} \sum_{\iota=1}^{n} \sum_{j=1}^{n} \gamma_{ij} lnp_\iota\, lnp_j \tag{2}$$

$$b(p) = \prod_{\iota=1}^{n} p_\iota^{\beta_\iota}, \tag{3}$$

while the overall price aggregator $\lambda(p)$ is an homogeneous function of degree zero defined as:

$$\lambda(p) = \sum_{\iota=1}^{n} \lambda_\iota ln\, p_\iota. \tag{4}$$

From (2), by applying the Roy's identity, we represent the budget share w_ι that the HHs allocates to the consumption group ι with:

$$w_\iota = \alpha_\iota + \sum_{j=1}^{n} \gamma_{\iota j} lnp_j + \beta_\iota ln\left[\frac{m}{a(p)}\right] + \frac{\lambda_\iota}{b(p)} \left\{ ln\left[\frac{m}{a(p)}\right] \right\}^2. \tag{5}$$

In this setting, demographic shifters can also be included in the analysis with the intercept, as follows: $\alpha_\iota = \alpha_{0\iota} + \sum_{q=1}^{Q} \alpha_{q\iota}\theta_q$, with θ_q representing a vector of *Q* socio-demographic regressors. Moreover, in order to be consistent with the utility maximization theory, the adding-up, homogeneity and symmetry restrictions must hold[20] in the QUAIDS estimation.

[19] We avoid the subscript of HH identification for simplicity's sake.

[20] The adding up holds for $\sum_{\iota=1}^{n} \alpha_\iota = 1$; $\sum_{\iota=1}^{n} \beta_\iota = 0$; $\sum_{\iota=1}^{n} \gamma_{\iota j} = 0$; $\sum_{\iota=1}^{n} \lambda_\iota = 0$. Moreover, in relation to demographic shifting, the homogeneity also implies that $\sum_{\iota=1}^{n} \alpha_{0\iota} = 1$; $\sum_{\iota=1}^{n} \alpha_{q\iota} = 1$, $\forall q$ (Attanasio et al., 2013).

A.2 Consumption quota, endogeneity sample selection and censoring

To account for the consumption quota we adapt the Deaton's (1981) framework following Wang and Chern (1992) and allowing equation (5) to vary as follows:

$$w_\iota = \alpha_\iota + \sum_{k=1}^{r} \rho_{\iota k} q_k + \sum_{j=1}^{n} \gamma_{\iota j} lnp_j + \beta_\iota ln\left[\frac{M}{a(p)}\right] + \frac{\lambda_\iota}{b(p)}\left\{ln\left[\frac{M}{a(p)}\right]\right\}^2, \tag{6}$$

where $w_\iota = p_\iota x_\iota / M$ and x_ι is the purchased quantity of commercial input ι; $M = m - \sum_{k=1}^{r} p_k q_k$, with$q_k$ and p_k, respectively, representing the constrained quantity and the redeeming price of the subsidized input k. Consequently, equation (2) now becomes:

$$ln\ a(p) = \alpha_0 + \sum_{k=1}^{r}\sum_{\iota=1}^{n}(\alpha_\iota + \rho_{\iota k} q_k) lnp_\iota + \frac{1}{2}\sum_{\iota=1}^{n}\sum_{j=1}^{n}\gamma_{ij} lnp_\iota\, lnp_j \tag{7}$$

With respect to the zero expenditure on several agricultural input items observed during the second stage of the budgeting process we follow Shonkwiler and Yen (1999). They proposed a two-step procedure with a bivariate probit estimation. In the first step, a binary outcome $\hat{d}_\iota$, equals one if the consumption of the input ι is positive, and zero otherwise, and is regressed on a vector of socio-demographic covariates ξ. In the second step, the normal probability density and the cumulative distribution of the probit are included in the quota constrained QUAIDS[21] thereby obtaining a modified version of equation (6) as follows:

$$w_\iota^* = \Phi(\xi' \hat{d}_\iota) w_\iota + \varphi_\iota \phi(\xi' \hat{d}_\iota). \tag{8}$$

Nevertheless, observing a censored outcome for a commercial agricultural input $\hat{d}_\iota$ is likely to be conditioned by receiving the voucher for the same input or not. This incidental truncation is dependent on households structural characteristics that affect their eligibility for the FISP; thus, we build four binary variables δ_k, one for each type of voucher k distributed, that assume value 1 if the HH received at least one coupon of type k and 0 otherwise. The probit estimation is thus conditioned by the selection equation:

$$\delta_k = \zeta_k' \psi_k + \omega_k, \tag{9}$$

where for each voucher type k, ζ_k is a vector of socio-demographic regressors affecting both inclusion in the FISP and $\hat{d}_\iota$, with the addition of an exogenous instrument for the model identification; ψ_k is a vector of parameters to be estimated and ω is an error term. Once calculated, the conditional probability density function for ϕ and Φ are included in the second stage of quota constrained QUAIDS following equation (8).

[21] Yen (2002) underlines how the deterministic part of the share equations does not add to unity under the censoring and so error terms do not add up to zero. The adding up restriction is thus not valid and the procedure of estimating n-1 equation is not necessary.

A.3 Income and price elasticities

In the first stage, conditional expenditure and price elasticities[22] are obtained differentiating system (8) with respect to $ln\, p_\iota$ and $ln\, m$ to obtain:

$$\mu_\iota \equiv \frac{\partial w_\iota^*}{\partial \ln(m)} = \left(\beta_\iota + \frac{2\lambda_\iota}{b(p)}\left\{\ln\left[\frac{m}{a(p)}\right]\right\}\right) \tag{10}$$

$$\mu_{\iota j} \equiv \frac{\partial w_\iota^*}{\partial \ln(p_j)} = \left(\gamma_{\iota j} - \mu_\iota\left(\alpha_j + \sum_g \gamma_{jg} \ln(P_g)\right) - \frac{\lambda_\iota \beta_j}{b(p)}\left\{\ln\left[\frac{m}{a(p)}\right]\right\}^2\right) \tag{11}$$

where P_g is a price index equal to the arithmetic mean of prices for all the g basic consumption groups in the analysis. Conditional expenditure elasticities are calculated by $\eta_\iota = \mu_\iota / w_\iota^* + 1$, while the Marshallian price elasticities are $\eta_{\iota j} = \mu_{\iota j}/w_\iota^* - \delta_{\iota j}$, where δ is the Kronecker delta assuming value 1 for $\iota = j$ and 0 otherwise (Edgerton, 1997). During the second stage, the same elasticities are also estimated by differentiating (8) and thus obtaining $\Phi(\xi_\iota' \hat{d}_\iota)\mu_\iota$ and $\Phi(\xi_\iota' \hat{d}_\iota)\mu_{\iota j}$, respectively. In the second stage, we can also evaluate the following elasticities, related to the quota level change:

$$z_{\iota k} \equiv \frac{\partial w_\iota^*}{\partial \ln(P_g)} = \Phi(\xi_\iota' \hat{d}_\iota)\left(\frac{\rho_{\iota k} q_k}{w_\iota} + \frac{\beta_\iota}{w_\iota}\left\{\frac{p_k q_k}{(m - \sum_{k=1}^{r} p_k q_k)}\right\}\right) \tag{12}$$

This represents the percentage variation of commercial input ι expenditure as the level of subsidized input k varies. These elasticities are particularly useful in our framework to evaluate how the expenditure on commercial inputs changes as the vouchers are distributed differently after the new targeting criteria.

[22] We concentrate on Marshallian elasticities since they measure the relationship between price and consumption for a given level of income, thereby capturing the variation in household real income as prices change. In cash-constrained situations, as in Malawi, the Marshallian elasticities are of greater interest (Ecker and Qaim, 2011).

Appendix B

Let y_i^* be the unobserved frontier equal to:

$$y_i^* = \alpha + x_i'\beta + v_i, \tag{13 }$$

$$v_i \sim \mathcal{N}^+(0, \sigma_v^2) \tag{14 }$$

The observed log output level $y_i$of the HH i is equal to y_i^* less the one-sided error $u_i > 0$. The resulting stochastic frontier model is:

$$y_i = \alpha + x_i'\beta + v_i - u_i, \tag{15 }$$

where x represents the logarithm of a vector of agricultural inputs and β is a vector of unknown parameters to be estimated; v_i and u_i are independent of each other and *i.i.d*. across observations. Moreover, to account for the heteroscedasticity of u_i and include the drivers of inefficiency, we follow the specification of Wang and Schimdt (2002) with $u_i \sim \mathcal{N}^+(\mu_i, \sigma_u^2)$ being a truncated normal distribution[23] with both the mean and the variance parameters scaled by the positive monotonic function $h(z_i, \gamma)$. This framework allows for explicit modelling of z_i through a vector of exogenous variables that influence farmer inefficiency and a vector of unknown parameters γ to be estimated.

[23] Several distributional specifications such as half normal, exponential or gamma can be utilized for the inefficiency error (Aigner, 1977; Meuusen and van den Broeck, 1977; Stevenson, 1980; Greene1980; Greene, 2003). For our purpose of identifying the determinants of inefficiency, the truncated normal distribution is the more appropriate because it can be used to model both mean and variance of the error term as dependent on exogenous covariates. However, for the purposes of robustness on the production function part, other distributions have been estimated. These are available upon request.

Appendix C

Table C.1 reports the estimation of the probit model for zero consumption of commercial inputs conditional to the sample selection caused by participation in the FISP and the redeeming of vouchers. Following the literature (Lunduka et al., 2013; Dorward et al., 2013; Chibwana et al., 2012), we utilize as covariates the exogenous determinants that the government declares must be included in the programme. We utilize the distance from the FISP outlet as an instrumental variable to identify the model exactly. This variable is expected to affect the redeeming possibility of farmers, but not their purchasing of commercial agricultural inputs, which can be done at any agricultural market. Tests for the validity of such instruments confirm its relevance.

Table C.1 Heckman probit selection for zero commercial input consumption and voucher eligibility with conditional PDFs

	(1) Maize		(2) Basal		(3) Urea		(4) Other fertilizers		(5) Other seeds	
main										
head_female	-0.074	(0.114)	-0.125**	(0.060)	-0.176**	(0.070)	-0.591***	(0.122)	-0.257**	(0.115)
head_age	0.123	(0.085)	0.084**	(0.041)	0.143***	(0.042)	0.148**	(0.071)	0.113	(0.075)
hhsize	0.029	(0.145)	0.213***	(0.082)	0.318***	(0.099)	0.029	(0.121)	0.307**	(0.143)
educ_15_60	0.377***	(0.137)	0.064	(0.074)	0.122	(0.078)	0.046	(0.110)	0.118	(0.131)
dist_agmrkt	-0.039	(0.073)	0.025	(0.052)	0.053	(0.055)	0.158***	(0.058)	0.010	(0.075)
sp_farm	0.226*	(0.135)	0.211***	(0.064)	0.118	(0.079)	0.248**	(0.100)	0.163	(0.138)
wealth: 1	-0.889***	(0.101)	-0.593***	(0.098)	-0.546***	(0.087)	-0.535***	(0.108)	-0.556***	(0.124)
wealth: 2	-0.989***	(0.113)	-0.179**	(0.091)	-0.250**	(0.097)	-0.251***	(0.091)	-0.537***	(0.114)
wealth: 3										
soil_quality: fair	-0.185	(0.133)	-0.095	(0.083)	-0.038	(0.087)	0.192	(0.137)	-0.392***	(0.125)
soil_quality: poor	-0.082	(0.126)	0.069	(0.082)	0.122	(0.090)	0.132	(0.135)	-0.399***	(0.122)
soil_type: good										
year	0.234***	(0.044)	0.014	(0.109)	0.067	(0.144)	-0.112*	(0.067)	0.388***	(0.060)
_cons	-472.056***	(88.064)	-28.167	(218.424)	-135.220	(289.205)	222.394*	(135.159)	-783.503***	(120.249)
Selection: voucher	maize		basal		urea		basal +urea		other seeds (flexi)	
head_female	0.081*	(0.047)	0.030	(0.060)	0.010	(0.062)	0.016	(0.056)	0.091*	(0.052)
head_age	0.024	(0.034)	-0.009	(0.035)	-0.019	(0.039)	-0.012	(0.036)	0.023	(0.034)
hhsize	0.007	(0.069)	0.233***	(0.075)	0.364***	(0.076)	0.225***	(0.072)	0.006	(0.069)
educ_15_60	-0.044	(0.058)	0.007	(0.059)	0.081	(0.065)	0.035	(0.061)	-0.044	(0.058)
dist_agmrkt	-0.082*	(0.043)	0.036	(0.044)	0.083**	(0.040)	-0.018	(0.046)	-0.082*	(0.043)
sp_farm	-0.308***	(0.059)	-0.323***	(0.061)	-0.312***	(0.057)	-0.306***	(0.057)	-0.307***	(0.059)
wealth: 1	-0.093	(0.064)	-0.175***	(0.067)	-0.144**	(0.068)	-0.196***	(0.067)	-0.094	(0.065)
wealth: 2	-0.021	(0.063)	0.048	(0.066)	0.024	(0.065)	-0.007	(0.064)	-0.022	(0.064)
wealth: 3										
soil_quality: fair	-0.100	(0.068)	-0.041	(0.067)	-0.032	(0.074)	0.004	(0.073)	-0.098	(0.068)
soil_quality: poor	-0.078	(0.064)	0.006	(0.060)	0.018	(0.069)	0.042	(0.062)	-0.076	(0.064)
soil_type: good										
year:	-0.343***	(0.024)	-0.465***	(0.025)	-0.515***	(0.023)	-0.425***	(0.024)	-0.342***	(0.024)
dist_admarc	-0.103*	(0.053)	-0.058	(0.049)	-0.083*	(0.046)	-0.145**	(0.056)	-0.102*	(0.053)
_cons	689.216***	(49.138)	935.774***	(51.207)	1035.246***	(45.942)	854.177***	(48.370)	688.805***	(49.147)
athrho										
_cons	0.246**	(0.104)	1.031***	(0.399)	0.782*	(0.457)	0.836*	(0.509)	0.395**	(0.186)
ϕ	0.392	(0.013)	0.283	(0.031)	0.282	(0.030)	0.110	(0.072)	0.156	(0.119)
N	4032		4032		4032		4032		4032	
ll	-2775.854		-3139.375		-3053.284		-2827.297		-2775.320	
chi2	212.464		117.184		163.878		111.830		100.534	
p	0.000		0.000		0.000		0.000		0.000	

Note: District clustered standard errors in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$; test for weak instrument: H0: dist_admarc=0, (1) chi2=0.51, p>chi2=0.476, (2) chi2=1.43, p>chi2=0.231, (3) chi2=2.16, p>chi2=0.095, (4) chi2=0.70, p>chi2=0.403, (5) chi2=0.29, p>chi2=0.593 ; ϕ= conditional PDF with SD in parenthesis.

Source: Authors' own elaboration.

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