Farm input subsidies and the adoption of natural resource management technologies

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Abstract

Farm input subsidies are often criticized to be economically and ecologically unsustainable. The promotion of natural resource management (NRM) technologies are widely seen as more sustainable to increase agricultural productivity and food security. However, relatively little is known about how input subsidies affect farmers' decisions to adopt NRM technologies. There are concerns of incompatibility, because NRM technologies are one strategy to reduce the use of external inputs in intensive production systems. However, in smallholder systems of Africa, where the average use of external inputs is low, there may possibly be interesting complementarities. Here, we analyze the situation of Malawi's Farm Input Subsidy Program (FISP). Using panel data from smallholder farm households, we develop a multivariate probit model and examine how FISP participation affects farmers' decisions to adopt various NRM technologies, such as intercropping of maize with legumes, use of organic manure, water conservation practices, and vegetative strips. As expected, FISP increases the use of inorganic fertilizer and improved maize seeds. Yet, we also observe a positive association between FISP and the adoption of certain NRM technologies. For other NRM technologies we find no significant effect. We conclude that input subsidies and the promotion of NRM technologies can be compatible strategies.

Keywords: fertilizer subsidy, technology adoption, sustainable agriculture, small farms, Africa, Malawi

1 Introduction

Agricultural input subsidies have had a long and controversial history in sub-Saharan Africa, but have experienced a revival during the last decade (Denning et al. 2009). Malawi has been a pioneer in the reintroduction of large-scale input subsidies (Chirwa and Dorward 2013). Instead of market-wide subsidies, which were common in the past, a targeted, voucher based approach was launched. Since 2005/06, Malawi's Farm Input Subsidy Program (FISP) targets poor smallholder farmers with vouchers for inorganic fertilizer and improved crop seeds with the intention to raise national and household food security. Especially in its early years, FISP was praised as a success story. Malawi experienced bumper harvests, and the overall wellbeing of smallholders seemed to increase with improved access to subsidized inputs and technologies (Lunduka et al. 2013). FISP became a role model for an African Green Revolution that many other African countries wanted to replicate (Denning et al. 2009; Lunduka et al. 2013).

However, more recently FISP has drawn substantial criticism in academic and policy arenas. Serious doubts have been raised concerning the Program's profitability, efficiency, and financial sustainability (MaSSP 2014). Recent studies showed low benefit-cost ratios and disappointing rates of return on subsidized fertilizer (Jayne et al. 2013; Lunduka et al. 2013). Moreover, the Program's ecological and social sustainability has been questioned by some (MaSSP 2014). Environmental NGOs in particular maintain that the use of agro-chemicals destroys the environment and contributes to small farmers' dependencies (Greenpeace Africa 2015). Also beyond NGO circles, there is broad agreement that sustainable productivity increases cannot build on input intensification alone, but that natural resource management (NRM) technologies, such as soil and water conservation practices, will have an important role to play (Marenya et al. 2012; The Montpellier Panel 2013; MaSSP 2014). Further development and wider adoption of NRM technologies could increase agricultural productivity, reduce environmental externalities, and make farming in Africa more resilient (Holden and Lunduka 2013).

With support from international donors, the Malawian government recently launched the Agricultural Sector-Wide Approach, a program to harmonize FISP with other policy initiatives that promote the dissemination and adoption of NRM technologies (MoAFS 2011). Yet, NRM technologies are often seen as a strategy to reduce the use of external inputs (Lee 2005), so it is unclear how compatible input subsidies and policies to promote NRM technologies actually are. Empirical evidence on how FISP might affect the adoption and use of NRM technologies is scarce. A few studies investigated the effect of FISP on cropland allocation with mixed results. Karamba (2013) and Holden and Lunduka (2010) suggested that FISP contributes to crop diversification and a decreasing share of land allocated to maize, while Chibwana et al. (2012) found evidence of less diversified cropping patterns. Holden and Lunduka (2012) analyzed the relationship between fertilizer subsidies and the use of organic manure and observed a positive link. Other than for these relationships no studies have analyzed the effects of input subsidies on the adoption of other soil and water conservation practices, such as maize intercropping with legumes, soil ridges, terraces, or vegetative strips, in Malawi or elsewhere. Here, this research gap is addressed.

In particular, panel data from smallholder maize producers, which was collected in 2011 and 2013, is used to analyze how FISP affects farmers' adoption of different NRM technologies. Two specific research questions are investigated: Does FISP participation influence the use of NRM technologies, specifically soil and water conservation practices? And more generally, is the adoption of input-intensive technologies compatible with the adoption of NRM technologies? To answer these questions a multivariate probit model that takes explicit account of the correlation between different adoption decisions is developed and estimated. The possible unobserved heterogeneity and selection bias of FISP participation is tested and controlled for with a Mundlak approach.

The rest of this paper is organized as follows. The next section provides some background on farming in Malawi and FISP. The paper then introduces the methods used, before it presents and discusses the estimation results. The final section concludes.

2 Malawi and FISP

Agriculture accounts for 30 per cent of Malawi's gross domestic product; about 90 per cent of the population are engaged in agricultural activities (CIA 2015). Maize is the main staple food and is grown on 70 per cent of the total cultivated land (Chirwa and Dorward 2013). Maize cultivation predominantly depends on rainfall with only one rainy season from December to April. The risk of crop failure due to drought and waterlogging is high. Input intensity among smallholders is relatively low, and the heavy reliance on maize cultivation further decreases soil fertility. Malawi's smallholder farmers regularly fall short of maize between January and March, when the stocks are decreasing. Rural households frequently suffer from severe food shortages (Denning et al. 2009). These circumstances have led to the implementation of input subsidy programs in the past and present (Chirwa and Dorward 2013).

FISP has been the latest addition to such policy initiatives aimed at increasing smallholder productivity, incomes, and food security (Lunduka et al. 2013). FISP targets about 50 per cent of Malawi's farmers with vouchers for subsidized inputs. In 2012/13, eligible households were supposed to receive two vouchers for fertilizer and one for improved maize seeds. Each fertilizer voucher could be redeemed for one 50 kg bag of fertilizer at a small fee of 500 MK (Malawi Kwacha). Seed vouchers could be redeemed cost-free for 5 kg of hybrid maize seeds or 8 kg of open-pollinated variety (OPV) seeds. Additionally, vouchers for legume seeds were available. Over time, other subsidy components such as fertilizer for tobacco, tea, and coffee, as well as cotton seeds and chemical treatments were also added, but the core package of inorganic fertilizer and improved maize seeds remained in place (Chirwa and Dorward 2013).

Since 2009/10, the government has allocated the vouchers proportionally to the number of farm families within districts. Distribution across villages is executed by government extension services and local authorities. Within villages, potential beneficiaries are identified in open forum allocations. Eligible farm households must fulfill at least one of the following criteria (Chirwa and Dorward 2013). They are (i) resource poor, but own and cultivate a piece of land, (ii) longtime residents of the village, (iii) guardians looking after physically challenged or HIV/AIDS-affected persons, or (iv) especially vulnerable, such as farm families headed by women or elderly individuals (Chirwa and Dorward 2013). In short, FISP intends to benefit poor and vulnerable farm households that are able to make productive use of the inputs provided (Chibwana et al. 2014). However, the actual practice of targeting and voucher allocation has been criticized for inconsistencies (Chirwa and Dorward 2013; Lunduka et al. 2013).

Program costs are also an issue of concern. In 2011/12, FISP accounted for 140 million US$, equivalent to almost 50 per cent of Malawi's agricultural budget (Chirwa and Dorward 2013). These high costs have led to questions about the Program's financial sustainability. Investigations also led to mixed evidence on the Program's effectiveness and economic impact; while returns were shown to be positive at national level, farm level returns seem to be rather modest (Lunduka et al. 2013). This has also contributed to international donors now putting more emphasis on sustainable land management (Holden and Lunduka 2012). NRM practices were identified as a major strategy for sustainably increasing productivity on smallholder farms (Sauer and Tchale 2009). Against this background, better integrating input subsidies with approaches to promote NRM technologies seems to be a necessity to reach FISP's goals in the medium and long run (Holden and Lunduka 2012).

3 Materials and methods

3.1 Data

The data used for this study come from a farm household survey that was conducted in two rounds in collaboration with the International Maize and Wheat Improvement Center (CIMMYT) and the Malawian Department of Agricultural Research Services (DARS). The survey covers data for two cropping seasons, 2009/10 and 2012/13, and was implemented in six districts of Malawi, namely Lilongwe, Kasungu, Mchinji, Salima, and Ntcheu in the Central, and Balaka in the Southern region of the country. These six districts were selected purposively based on their maize production potential. A multistage proportionate random sampling procedure was then applied to select villages in each district and households in each village. In the first survey round 890 households were interviewed. Out of these, in the second round 757 were re-interviewed. Some sample attrition occurred, as is normal for panel survey rounds with several years in-between. Hence, the econometric analysis is based on an unbalanced panel and pooled observations from both rounds. Households with missing data were excluded. The final data set consists of 1482 observations. The empirical models draw on detailed information at the household and plot level and has a strong focus on the farms' agricultural production systems.

3.2 Multivariate probit model of technology adoption

Smallholder farmers have to deal with multiple agricultural production constraints affecting their households' wellbeing. Farmers often use different strategies and technologies, whereby the adoption of one technology cannot be seen in isolation from other technologies and inputs used. The possibility that adoption decisions are interrelated has recently drawn a lot of attention (e.g., Kassie et al. 2013; Kassie et al. 2015; Wainaina et al. 2016). The adoption of multiple technologies can result in complementarities and tradeoffs, meaning that some combinations make more sense for farmers than others. A modeling approach that takes into account the complex decision-making in technology adoption is the multivariate probit model (MVP). The MVP simultaneously models the adoption of a set of technologies. In contrast to standard probit models with only one dependent variable, the MVP accounts for relationships between different technologies that can lead to correlation of unobserved factors and the error term in the adoption equations (Greene 2012).

The current paper uses an MVP to explain the adoption decisions for multiple innovations, including input-intensive and NRM technologies, and assess the role of FISP participation in these decisions. The general model can be written as follows:

$$TA_k^* = \beta_0 + \beta_{1k}FISP + \beta_{2k}H + \beta_{3k}R + \beta_{4k}T + \varepsilon_k \quad (1)$$

$$TA_k = \begin{cases} 1 \; if \; TA_k^* > 0 \\ 0 \; otherwise \end{cases} \quad (2)$$

where TA_k* denotes a latent variable that can be understood as the expected net benefit from adopting technology *k*. The model considers 7 different technologies as will be detailed below. TA_k* is assumed to be a linear combination of explanatory variables and the unobserved error term ε. Given that TA_k* is not observable, model estimation is based on the observed binary variable TA_k, which describes whether or not a farm household has adopted technology *k.*

The main explanatory variable of interest in this study is $FISP_k$, which is a dummy for participation in the subsidy program, meaning that a household actually received vouchers for inorganic fertilizer and improved maize seeds. The effect of participation on technology adoption is measured by β_{1k}. A positive (negative) and significant coefficient β_{1k} would indicate that the input subsidy increases (decreases) the probability of adoption of technology *k*. In addition, a range of farm and household characteristics (*H*), regional characteristics (*R*), and a year dummy (*T*) for the survey round are included.

The error terms in the MVP model jointly follow a multivariate normal distribution with zero conditional mean and variance normalized to unity. The model generates a variance-covariance matrix that denotes the correlation of the error terms for any two equations (Kassie et al. 2013). This matrix allows us to describe the correlation between all technologies considered. Complementary technologies have a positive correlation, while negative correlations might indicate a substitutive relationship.

3.3 Addressing unobserved heterogeneity and potential selection bias

The particular design of FISP provides a challenge for empirical analysis, as the targeting process is non-random and can therefore lead to selection bias in the estimation of equation (1). Selection into FISP and the decision to adopt NRM technologies could be jointly determined by the same unobserved household characteristics, such as farm management ability or a farm household's motivation. For instance, among the large number of potential beneficiaries of FISP, farms with higher management ability may have a greater chance to be selected because they are assumed to make better use of fertilizer and improved seeds. At the same time, these farmers may also be more innovative and thus more likely to adopt NRM technologies at an early stage. Unless controlled for, such unobserved characteristics can cause bias in the estimated effect of FISP participation.

Earlier studies that have analyzed the effects of FISP have used instrumental variable (IV) approaches to control for unobserved heterogeneity and reduce selection bias (Ricker-Gilbert et al. 2011; Lunduka et al. 2013; Karamba 2013). However, the identification of reliable instruments is challenging and the implementation of IV procedures in a multivariate probit framework is not established yet. Another way to address this issue is to exploit the panel nature of one's data, and use fixed effects models. Yet, there are two shortcomings of using fixed effects within a multivariate probit approach: (1) the binary nature of the outcome variables might result in the incidental parameter problem (Greene 2012); (2) a fixed effects procedure would require the estimation of single adoption models and neglect the relationships between different technologies as explained above. As an alternative, the MVP model can be modified using an approach proposed by Mundlak (1978), which requires the inclusion of the means of all time-varying explanatory variables $\overline{X}$ (including FISP participation, household characteristics and regional characteristics), and can be written as follows:

$$TA_k^* = \beta_0 + \beta_{1k}FISP + \beta_{2k}H + \beta_{3k}R + \beta_{4k}T + \beta_{5k}\overline{X} + \varepsilon_k \qquad (3)$$

Including the means of these variables gives the fixed-effects estimates (Mundlak 1978), controls for unobserved heterogeneity and addresses the selection bias in the MVP model (Kassie et al. 2015).

4 Results

4.1 Descriptive statistics

Descriptive statistics of explanatory variables in the regression models are shown in Table 1. Farms are relatively small with an average farm size of 3.3 acres. Fifty percent of the sample households had participated in FISP during the seasons covered by the two survey rounds, meaning that they received vouchers for subsidized fertilizer and maize seeds. Among the household characteristics used in the regression models are typical human capital variables – such as age, education, and gender of the household head – as well as assets – such as farm size and livestock ownership – that were shown to affect technology adoption in many situations. Moreover, a number of social capital and social network variables are considered as well as shocks experienced in the past, as these can also influence technology adoption significantly (Doss 2006; Kassie et al. 2015). Regional factors include infrastructure conditions, district-level population size, and a geographical dummy, among others.

Table 1: Descriptive statistics for explanatory variables used

Variable	Description	Mean	SD
Household characteristics			
FISP	Household has participated in FISP during the last season	0.50	(0.50)
Age	Household head age (years)	44.70	(14.75)
Female head	Household head female (dummy)	0.15	(0.36)
Education	Household head education (years)	5.24	(3.51)
Adults	Adult household members, ≥ 15 (number)	2.85	(1.31)
Children	Child household members, ≤ 12 (number)	2.01	(1.41)
Resources			
Asset value	Total value of major farm and household equipment (‘000 MK)	37.81	(144.37)
Livestock	Number of livestock (Tropical Livestock Units)	1.24	(2.75)
Farm size	Farm land owned (acres)	3.30	(2.79)

Table 1 continued

Variable	Description	Mean	SD
Business	Own business income (dummy)	0.46	(0.50)
Seasonal labor	Seasonal labor income (dummy)	0.59	(0.49)
Remittances	Income through remittances (dummy)	0.28	(0.45)
Credit access	Access to credit (dummy)	0.22	(0.41)
Previous subsidy recipient	Household has received subsidies in all previous seasons of FISP operation (dummy)	0.19	(0.39)
Shocks			
Socioeconomic shocks	Household experienced agricultural input shortage and food insecurity during the past ten years (dummy)	0.85	(0.36)
Water stresses	Household experienced drought or waterlogging during the past ten years (dummy)	0.75	(0.43)
Pests and diseases	Household experienced agricultural pests and diseases during the past ten years (dummy)	0.48	(0.50)
Social capital/network			
Social group member	Membership in church, women's, or other social groups (dummy)	0.51	(0.50)
Relatives in village	Household can rely on relatives in the village (number)	4.09	(4.20)
Traders in village	Household trusts grain traders in the village (number)	1.94	(3.31)
Farmers' group member	Membership in farmers', input or marketing group (dummy)	0.10	(0.30)
Leadership connections	Relative of household holds leadership position (dummy)	0.53	(0.50)
Relatives outside village	Household can rely on relatives outside the village (number)	4.16	(4.51)
Traders outside village	Household trusts grain traders outside the village (number)	4.69	(5.56)
Government support	Household can rely on government when crop fails (dummy)	0.58	(0.49)
Years in village	Years the household has resided in the same village	28.71	(17.97)
Access to services			
Market distance	Distance to the main market (walking minutes)	88.11	(67.45)
Main road passable	Main road passable by cars for more than half the year (dummy)	0.91	(0.29)
Extension	Household benefitted from agricultural extension (average number of days per season)	1.73	(3.80)
Village characteristics			
Farm families in district	Total number of farm families residing in district ('000)	23.01	(7.48)
DPP	Ruling party, DPP, won district in 2009 election (dummy)	0.54	(0.50)
Southern	Household resides in the Southern region (dummy)	0.18	(0.38)
Year	Survey year 2013 (dummy)	0.46	(0.50)

Notes: The number of observations is 1482. All data are from the farm household survey, except for farm families in district, which were obtained from the Ministry of Agriculture and Food Security, and DPP, which reflects the 2009 election results as obtained from the Malawi Electoral Commission.

The technology adoption variables considered in this study comprise 7 different technologies, namely (i) inorganic fertilizer and (ii) improved maize seeds as two input-intensive technologies; and (iii) legume intercropping, (iv) manure, (v) soil ridges, (vi) terraces and stone bunds, and (vii) vegetative strips as five NRM technologies. Table 2 presents descriptive statistics for these 7 technologies.

Table 2: Adoption of different technologies by participation in input subsidy program

Technology	Description	Adoption rate All (n=1482)	FISP (n=744)	Non-FISP (n=738)
Inorganic fertilizer	Farmer applied inorganic fertilizer (= 1, otherwise 0)	0.942	0.996	0.887****
Improved maize	Farmer used improved maize varieties (= 1, otherwise 0)	0.779	0.871	0.687****
Legume intercropping	Farmer practiced legume intercropping (= 1, otherwise 0)	0.306	0.353	0.257****
Manure	Farmer used manure (= 1, otherwise 0)	0.384	0.379	0.389
Ridges	Farmer constructed ridges (= 1, otherwise 0)	0.560	0.559	0.561
Terraces and stone bunds	Farmer constructed terraces and stone bunds (= 1, otherwise 0)	0.152	0.142	0.160
Vegetative strips	Farmer used vegetative strips (= 1, otherwise 0)	0.195	0.215	0.175**

Notes: Differences between FISP and Non-FISP farmers were tested for statistical significance. ****P≤0.001, ***P≤0.01, **P≤0.05, *P≤0.1

The use of inorganic fertilizer and improved maize seeds is widespread in Malawi. In comparison, many of the NRM technologies are used less widely, although some have also been adopted by a considerable proportion of farmers. For instance, legume intercropping is practiced by almost one-third of the households. In Malawi, the use of pigeon pea, groundnut, soybean, and other bean species as intercrops is a common practice among farmers who want to diversify their cropping systems (Gilbert 2004). These legumes do not only fix atmospheric nitrogen, but they are also capable of exploiting residual moisture in the soil, so that intercropping with maize can be advantageous. In addition, intercropping can provide benefits in terms of soil organic matter and lower problems with pests (Tilman et al. 2002; Snapp et al. 2010). Use of organic manure is also quite common in Malawi, even though the quantities applied are typically low (Holden and Lunduka 2012).

Of particular interest among the NRM technologies are also soil and water conservation practices that can help to increase soil water availability, decrease soil erosion, and maintain nutrient levels (Delgado et al. 2011). In Malawi, soil ridges were already promoted during colonial times and in the post-independence era (Kassie et al. 2015), which is why over half of all farmers are using this practice. Ridges are soil embankments that run along the contour of a plot and thus slow down water runoff and sediment wash out. The size and the spacing of ridges can vary depending on slope and other factors. Ridges are usually renewed every season. In contrast, terraces and stone bunds, which serve a similar purpose as soil ridges, are longer-term structures involving higher investments for building (Critchley et al. 1994). Stone bunds are semi-permeable barriers; excess runoff water can pass through and is filtered, so that sediments are caught. Filtration also promotes leveling off the field behind the stone bunds and the formation of terraces. Around 15 per cent of the sample farmers have constructed terraces and stone bunds. They are commonly found on hillsides where stone is abundant. Vegetative strips are used to control runoff and soil erosion. For instance, vetiver grass is traditionally used for soil conservation; trees or shrubs might serve as living fences around cultivated fields to protect against erosion (Critchley et al. 1994).

Table 2 also compares technology adoption rates between FISP participants and non-participants. The use of inorganic fertilizer and improved maize seeds is significantly higher among FISP participants, which is unsurprising. Strikingly, however, not all program participants use improved maize seeds. For most of the NRM technologies, no significant differences can be observed. Only for legume intercropping and vegetative strips we observe higher adoption rates among FISP participants. This is a first indication that FISP and the promotion of NRM technologies are not incompatible, which is analyzed in more detail in the following paragraphs.

4.2 FISP participation

Before analyzing the effect of participation in the subsidy program on the adoption of NRM technologies, a probit model will explain participation in the FISP. Looking more closely at the factors that influence participation is interesting because it explains the functioning of the selection process into the subsidy program. Of particular interest are variables that capture the targeting criteria of FISP, such as age and gender of the household head, exposure to past shocks, and wealth status. Other studies have also shown that social networks and political factors may also play a role for beneficiary selection and could influence voucher allocation (Mason and Ricker-Gilbert 2013). Such factors are also captured in the model.

Table 3 presents the estimates for the model to explain participation in FISP. The results suggest that older household heads are more likely to participate in FISP than younger farmers. This is in accord with the FISP guidelines that mention elderly-headed households as priority beneficiaries. The marginal effect for female household head is also positive, but not statistically significant. Education has a positive effect that is significant at the 10 per cent level. In contrast to Chibwana et al. (2012), who suggested that better-off households may benefit more from FISP, we find asset values to be negatively associated with FISP participation, meaning that poorer households are more likely to benefit from input subsidies. Eligibility is confined to households with own land. Our results show that farm size has a positive effect on the likelihood of participation, but this effect is diminishing with increasing farm size, as indicated by the negative square term. The turning point is reached at a farm size of 9.8 acres, which is still within the range of hand-hoe based smallholder farms, which are defined in Malawi up to a size of 12.5 acres (Holden 2014).

Table 3: Factors influencing FISP participation

Explanatory variables	Marginal effects	P-value
Age	0.003	0.034
Female head	0.051	0.248
Education	0.008	0.085
Adults	0.000	0.979
Children	0.012	0.247
Asset value	-0.000	0.005
Livestock	-0.003	0.507
Farm size	0.033	0.012
Farm size, squared	-0.002	0.015
Socioeconomic shocks	0.129	0.001
Previous subsidy recipient	0.307	0.000
Business	0.032	0.260
Seasonal labor	0.008	0.792
Remittances	0.051	0.107
Years in village	0.002	0.075
Social group member	0.063	0.071
Relatives in village	0.005	0.149
Traders in village	0.010	0.032
Leadership connections	0.013	0.653
Main road passable	-0.005	0.915
Farm families in district	-0.002	0.448
DPP	0.130	0.000
Southern	0.195	0.000
Year	-0.021	0.567
Pearson's goodness-of-fit statistic, prob>χ^2	0.51	
Percent correctly classified	65.52	

Notes: The number of observations is 1482. P-values are based on robust standard errors, adjusted for 827 household clusters.

Table 3 also shows that past socioeconomic shocks increase the likelihood of FISP participation, implying that vulnerable households are included. Households that have received subsidies continuously in previous years are more likely than other households to participate in FISP also in the current season. Chirwa et al. (2013) argue that sustainable graduation from the subsidy program has been difficult especially for poorer households, thus remaining regular subsidy recipients. Social networks in the village also have a positive effect, as shown by the estimation results for membership in social groups and trust in village traders. Years in village is also significant; households that have resided longer in the same village might be more well-known to village leaders and have better chances to be selected as FISP beneficiary (Chibwana et al. 2013). Social networks likely play a role during the process of beneficiary selection at local levels. The DPP dummy also has a positive effect on the likelihood of FISP participation, suggesting that political motives may play a role in voucher allocation. This is in line with findings from Mason and Ricker-Gilbert (2013). Finally, households living in the Southern region are more likely to participate in FISP than households from the Central region. Poverty rates in the South of Malawi are higher than in other parts of the country.

In summary, the estimation results in Table 3 suggest that productive but asset-poor and vulnerable farm households are those who participate in the subsidy program with higher probability. In other word, FISP targeting seems to function reasonably well. Nevertheless, there seem to be some social and political factors that might be fostered by unobservable household characteristics, and could influence the selection into FISP in an undesirable way.

4.3 MVP model results

4.3.1 Interrelationships between technologies

Before presenting the MVP results themselves, looking at the error term correlation matrix of the model will provide an idea of possible interrelationships in the adoption of different technologies. The results in Table 4 suggest that the null hypothesis of zero correlation between the error terms of all equations needs to be rejected. Hence, the MVP model that accounts for error term correlation is appropriate.

Most of the correlation coefficients in Table 4 have positive signs, suggesting that farmers in Malawi do not consider certain technologies as substitutes for others. One exception is the negative correlation between inorganic fertilizer and manure. Both inputs are used to enhance soil nutrients; manure additionally helps to improve soil organic matter. While both inputs can be used together, farmers in Malawi who adopted one are less likely to adopt the other, probably due to resource constraints. This was also observed by Wainaina et al. (2016) in Kenya.

Table 4: Correlation matrix for technology adoption equations

	Improved maize	Legume inter-cropping	Manure	Ridges	Terraces and stone bunds	Vegetative strips
Inorganic fertilizer	0.208*** (0.080)	0.009 (0.080)	-0.168** (0.078)	0.114 (0.076)	-0.083 (0.083)	0.186* (0.099)
Improved maize		0.017 (0.052)	0.091* (0.050)	-0.001 (0.048)	0.135** (0.062)	0.039 (0.054)
Legume intercropping			0.154**** (0.045)	0.253**** (0.046)	0.139** (0.055)	0.052 (0.052)
Manure				0.084* (0.043)	-0.025 (0.052)	0.136*** (0.050)
Ridges					0.035 (0.051)	0.012 (0.047)
Terraces and stone bunds						-0.004 (0.058)
Likelihood ratio test of all correlation coefficients jointly equal to zero: chi2(21) = 86.57****						

Notes: The number of observations is 1482. Robust standard errors are adjusted for 827 household clusters. ****P≤0.001, ***P≤0.01, **P≤0.05, *P≤0.1

Positive and significant correlation coefficients point at complementarities between technologies. The positive relationship between inorganic fertilizer and improved maize is expected and in line with previous studies (e.g., Denning et al. 2009; Kassie et al. 2013). Improved varieties are often more responsive than traditional landraces to fertilizer application. We also observe positive relationships between different NRM technologies, indicating that farmers pursue different strategies of soil and water conservation in conjunction. Strikingly, however, the correlation matrix in Table 4 shows significantly positive coefficients for a few combinations of input-intensive and NRM technologies, too. The results suggest that inorganic fertilizer is often adopted in combination with vegetative strips; improved maize seeds are used together with manure and with terraces and stone bunds. Similar complementarities between input-intensive and NRM technologies were also observed in other East African countries (Kassie et al. 2015;

Wainaina et al. 2016). These findings challenge the widely-held public belief that input-intensive and NRM technologies are incompatible.

4.3.2 FISP participation and technology adoption

We now turn to the results of the MVP model itself, which we use to analyze the influencing factors of farmers' technology adoption. The full estimation results are shown in Tables A1-A3 in the online appendix. Several variables related to human capital, asset ownership, social networks, institutions, and agroecological factors have significant effects. Certain factors, such as asset ownership, have a positive influence on the adoption of input-intensive technologies but a negative effect on the adoption of NRM practices. Other variables, such as membership in farmer groups, are positively associated with both types of technologies. We refrain from a detailed discussion of all influencing factors (see Kassie et al. 2013; and Kassie et al. 2015; Wainaina et al. 2016 for recent analyses of technology adoption), because the focus here is primarily on the effect of FISP participation on the use of NRM technologies.

Table 5 summarizes the influence of FISP participation on technology adoption using three different specifications of the MVP model: (i) The basic model includes FISP participation as a dummy variable without controlling for potential selection bias. (ii) The reduced model does not control for possible selection bias either, but only includes equations for the five NRM technologies; this specification serves to test whether the effects of FISP participation are sensitive to inclusion of the input-intensive technologies in the MVP model. (iii) In the Mundlak model, we control for possible selection bias from unobserved heterogeneity by including the means of all time-varying covariates as described in the *Materials and methods* section.

Results from the basic model in Table 5 show significantly positive effects of FISP participation on the use of inorganic fertilizer and improved maize seeds. This is unsurprising, as the subsidy program intends to promote the adoption of these technologies. From this perspective, FISP seems to be effective, which was also shown in previous research (Chibwana et al. 2014; Snapp and Fisher 2015). In addition, the basic model suggests significantly positive effects of

FISP participation on the adoption of some NRM technologies, as well. The positive effect on legume intercropping may be due to subsidized inputs contributing to higher productivity in maize (Chibwana et al. 2014). Some of the households that meet their subsistence needs of maize may decide to allocate more land to legumes (Karamba 2013), even though Chibwana et al. (2012) showed that this is not always the case. Another explanation is that FISP participants also received vouchers for improved legume seeds in some cases. The positive effect of FISP participation on the adoption of vegetative strips is not straightforward to explain, but underlines at least that input subsidies do not prevent farmers from using this agronomic technique. The reduced model confirms the results of the basic model without any considerable changes for the association between FISP participation and the adoption of NRM technologies. However, results from these two models should be interpreted with caution because of possible selection bias.

Table 5: Effects of FISP participation on technology adoption

	Inorganic fertilizer	Improved maize	Legume inter-cropping	Manure	Ridges	Terraces and stone bunds	Vegetative strips
Basic model	1.713****	0.688****	0.153**	-0.017	-0.031	-0.076	0.172**
	(0.262)	(0.083)	(0.075)	(0.073)	(0.073)	(0.088)	(0.081)
Log pseudo likelihood = -4920.34; Wald chi2(231) = 1025.78****							
Reduced model			0.155**	-0.018	-0.034	-0.079	0.167**
			(0.075)	(0.073)	(0.073)	(0.088)	(0.081)
Log pseudo likelihood = -3997.44; Wald chi2(165) = 637.36****							
Mundlak model	1.474****	0.421****	0.010	-0.113	-0.053	-0.117	0.111
	(0.344)	(0.127)	(0.115)	(0.104)	(0.113)	(0.141)	(0.128)
Joint significance of mean of time-varying covariates (chi2)	81.91****	49.20****	22.17	35.98	28.59	21.99	37.09
Log pseudo likelihood = -4806.52; Wald chi2(427) = 2541.23****							

Notes: The number of observations is 1482; the number of draws is 50 for each MVP model. Robust standard errors are adjusted for 827 household clusters. Full estimation results are shown in Tables A1-A3 in the appendix. ****P≤0.001, ***P≤0.01, **P≤0.05, *P≤0.1

The last line in Table 5 reports the results from the MVP model with Mundlak approach. The null hypothesis that all coefficients of the mean of time-varying covariates are jointly significantly equal to zero is rejected only for the inorganic fertilizer and improved maize equations, thus supporting the presence of unobserved heterogeneity and the use of Mundlak approach in these cases (Table 5). Results from the Mundlak model confirm the positive effect of FISP on the adoption of inorganic fertilizer and improved maize seeds, but the coefficient estimates are slightly smaller. This points to an upward bias of results if unobserved heterogeneity is not corrected for. The estimated effects for the adoption of NRM technologies are slightly different. While the coefficients in the legume intercropping and vegetative strips equations remain positive, they are now insignificant. The signs of the coefficient estimates for the other NRM technologies remain the same throughout all equations. Although the coefficient estimates for the NRM equations are insignificant in the Mundlak model, the results show at least that participation in the FISP has no negative effect on the adoption of NRM technologies in smallholder farms.

5 Conclusion

The Farm Input Subsidy Program (FISP) which was launched in Malawi in 2005/06 has contributed to bumper harvests and improved wellbeing of poor farm households. FISP has even inspired other African countries to also introduce large-scale input subsidy programs. However, in recent years FISP has been increasingly criticized for not being economically and ecologically sustainable. In particular, there are doubts that FISP is compatible with natural resource management (NRM) technologies that build on improved agronomic practices to raise productivity and conserve soil and water.

In this paper, panel data collected from smallholder farm households in Malawi was used to analyze the effect of FISP participation on the adoption of various technologies, and more generally the compatibility of input-intensive and NRM technologies. The results show that FISP participation significantly increases the farmers' likelihood to use inorganic fertilizer and improved maize seeds. This was expected, because FISP participants receive vouchers for the purchase of these modern inputs at subsidized rates. For the adoption of NRM technologies some positive effects of FISP are also reported. FISP participation is positively associated with the practice of legume intercropping and the use of vegetative strips. These effects are probably due to productivity increases in maize resulting from the use of subsidized inputs and a concomitant reallocation of land and other household resources. The effect of FISP on the adoption of other NRM technologies is not statistically significant. Independent of the subsidy program, the results indicate that farmers in Malawi tend to consider modern inputs and NRM practices as complementary, not as substitutes in most cases. Different types of technologies are often adopted in combination.

To control for unobserved heterogeneity bias and possible selection bias in the analysis, the multivariate probit model has also been estimated with Mundlak approach. Although, including Mundlak approach has changed the significance levels of FISP participation on legume intercropping and vegetative strips, the results remain robust in general. Therefore some cautious conclusions should be in order. The current study suggests that there are no inevitable policy tradeoffs between targeted input subsidy programs and the promotion of NRM technologies in smallholder farming systems. In fact, the use of NRM technologies in Malawi seems to be more common among subsidy recipients than among non-recipients. It can be argued that the promotion of complementary NRM technologies under FISP is feasible. However, further research is necessary to gain deeper understanding of the impact mechanisms and help design improved extension strategies to harness synergistic relationships between different types of technologies.

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Appendix

Table A1: Basic multivariate probit model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Explanatory variables	Inorganic fertilizer	Improved maize	Legume intercropping	Manure	Ridges	Terraces and stone bunds	Vegetative strips
FISP	1.713****	0.688****	0.153**	-0.017	-0.031	-0.076	0.172**
	(0.262)	(0.083)	(0.075)	(0.073)	(0.073)	(0.088)	(0.081)
Age	0.004	-0.005	-0.002	-0.003	0.006**	-0.009***	-0.003
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Female head	-0.261	0.079	0.273**	-0.009	-0.165	-0.005	-0.023
	(0.177)	(0.116)	(0.107)	(0.108)	(0.101)	(0.129)	(0.117)
Education	0.044**	0.015	0.000	0.010	0.012	-0.020	0.003
	(0.020)	(0.013)	(0.012)	(0.012)	(0.011)	(0.013)	(0.013)
Adults	-0.034	-0.042	0.067**	0.060**	0.013	0.025	-0.030
	(0.053)	(0.034)	(0.033)	(0.030)	(0.029)	(0.034)	(0.034)
Children	-0.002	0.058*	0.050*	0.033	-0.026	-0.041	0.040
	(0.050)	(0.031)	(0.027)	(0.027)	(0.026)	(0.031)	(0.029)
Asset value	0.005**	0.000	-0.002***	-0.001***	-0.000	-0.000	0.000
	(0.003)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Livestock	-0.011	0.012	0.018	0.073***	-0.003	0.006	0.017*
	(0.030)	(0.016)	(0.015)	(0.023)	(0.012)	(0.010)	(0.010)
Farm size	0.091	0.045	0.019	0.045	0.057**	0.050	0.123****
	(0.059)	(0.031)	(0.034)	(0.035)	(0.029)	(0.034)	(0.034)
Farm size, squared	-0.003*	-0.001	-0.003	-0.004*	-0.002	-0.002	-0.006****
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Socioeconomic shocks	-0.036	0.036	0.010	-0.171*	0.065	0.099	0.260**
	(0.191)	(0.109)	(0.101)	(0.097)	(0.097)	(0.114)	(0.120)
Business	-0.113	0.060	0.147**	0.061	0.119	-0.052	0.012
	(0.126)	(0.081)	(0.074)	(0.071)	(0.073)	(0.083)	(0.083)
Seasonal labor	-0.306**	-0.038	0.083	0.054	0.115	0.033	-0.157*
	(0.138)	(0.082)	(0.080)	(0.072)	(0.075)	(0.088)	(0.082)

Table A1 continued

Explanatory variables	(1) Inorganic fertilizer	(2) Improved maize	(3) Legume intercropping	(4) Manure	(5) Ridges	(6) Terraces and stone bunds	(7) Vegetative strips
Remittances	-0.010	-0.093	0.157*	0.109	-0.043	0.313****	0.085
	(0.156)	(0.089)	(0.082)	(0.076)	(0.073)	(0.087)	(0.087)
Credit access	0.187	-0.129	0.114	0.186**	0.091	0.211*	-0.054
	(0.173)	(0.107)	(0.093)	(0.091)	(0.091)	(0.108)	(0.101)
Social group member	0.133	-0.044	-0.006	0.050	-0.190**	0.070	-0.140
	(0.173)	(0.099)	(0.089)	(0.085)	(0.089)	(0.092)	(0.101)
Relatives in village	-0.000	0.013	-0.011	-0.001	-0.016*	0.001	0.008
	(0.017)	(0.011)	(0.010)	(0.009)	(0.009)	(0.011)	(0.010)
Traders in village	-0.002	-0.023*	0.008	0.007	-0.003	0.023*	0.023*
	(0.022)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Farmer’s group member	0.377	0.299**	0.023	-0.042	0.356****	0.415****	0.100
	(0.280)	(0.146)	(0.119)	(0.120)	(0.112)	(0.119)	(0.130)
Leadership connections	-0.128	0.025	0.041	0.177**	-0.134*	-0.046	0.098
	(0.136)	(0.081)	(0.076)	(0.071)	(0.073)	(0.086)	(0.079)
Relatives outside village	0.014	0.014	0.017*	-0.012	-0.018**	0.005	0.001
	(0.016)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Traders outside village	-0.009	0.022**	0.005	0.001	0.000	0.003	-0.004
	(0.013)	(0.009)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Government support	0.144	-0.054	0.052	-0.010	-0.359****	0.184**	-0.101
	(0.120)	(0.078)	(0.074)	(0.071)	(0.071)	(0.086)	(0.080)
Extension	0.028	0.010	0.006	0.016*	0.011	-0.007	0.024**
	(0.018)	(0.009)	(0.009)	(0.009)	(0.009)	(0.013)	(0.010)
Water stresses	0.086	-0.217**	0.126	0.098	0.306****	0.071	-0.177**
	(0.145)	(0.095)	(0.084)	(0.082)	(0.082)	(0.097)	(0.089)
Pests and diseases	0.009	-0.061	0.282****	0.113	-0.100	-0.024	0.162**
	(0.129)	(0.077)	(0.073)	(0.069)	(0.070)	(0.083)	(0.080)
Market distance	0.009****	-0.002	-0.000	0.001	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Market distance, squared	-0.000**	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table A1 continued

Explanatory variables	(1) Inorganic fertilizer	(2) Improved maize	(3) Legume intercropping	(4) Manure	(5) Ridges	(6) Terraces and stone bunds	(7) Vegetative strips
Main road passable	-0.007	-0.081	0.156	0.106	-0.052	-0.074	0.152
	(0.233)	(0.133)	(0.136)	(0.127)	(0.131)	(0.138)	(0.129)
Farm families in district	0.008	0.019***	0.003	0.004	0.006	-0.009	0.000
	(0.011)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
DPP	0.459**	-0.170*	0.255***	-0.155	0.210**	-0.092	-0.197**
	(0.185)	(0.099)	(0.097)	(0.096)	(0.090)	(0.105)	(0.100)
Southern region	-0.922****	0.153	0.243**	0.001	-0.305***	0.208	0.082
	(0.220)	(0.121)	(0.114)	(0.119)	(0.108)	(0.129)	(0.119)
Year	-0.748****	0.031	0.187*	0.103	0.496****	-0.078	0.211*
	(0.194)	(0.108)	(0.108)	(0.097)	(0.099)	(0.108)	(0.116)
Constant	0.418	0.309	-1.825****	-1.010****	-0.587**	-0.822***	-1.545****
	(0.497)	(0.320)	(0.300)	(0.282)	(0.274)	(0.316)	(0.320)

Notes: The number of observations is 1482. Pseudo log-likelihood: -4920.34; Wald chi2(427): 1025.78****; Number of draws: 50. Robust SEs, adjusted for 827 household clusters, in parentheses. ****P≤0.001, ***P≤0.01, **P≤0.05, *P≤0.1

Table A2: Reduced multivariate probit model

Explanatory variables	(3) Legume intercropping	(4) Manure	(5) Ridges	(6) Terraces and stone bunds	(7) Vegetative strips
FISP	0.155**	-0.018	-0.034	-0.079	0.167**
	(0.075)	(0.073)	(0.073)	(0.088)	(0.081)
Age	-0.002	-0.003	0.006**	-0.009**	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Female head	0.273**	-0.007	-0.161	-0.002	-0.022
	(0.107)	(0.109)	(0.101)	(0.129)	(0.117)
Education	0.000	0.010	0.012	-0.020	0.004
	(0.012)	(0.012)	(0.011)	(0.013)	(0.013)
Adults	0.067**	0.061**	0.014	0.024	-0.028
	(0.033)	(0.030)	(0.029)	(0.034)	(0.034)
Children	0.050*	0.032	-0.025	-0.040	0.040
	(0.027)	(0.027)	(0.026)	(0.031)	(0.029)
Asset value	-0.002***	-0.001***	-0.000	-0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Livestock	0.018	0.072***	-0.002	0.006	0.018*
	(0.015)	(0.023)	(0.012)	(0.010)	(0.010)
Farm size	0.019	0.044	0.056*	0.050	0.124****
	(0.034)	(0.035)	(0.029)	(0.034)	(0.035)
Farm size, squared	-0.003	-0.004*	-0.002	-0.002	-0.006****
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Socioeconomic shocks	0.010	-0.172*	0.066	0.091	0.259**
	(0.101)	(0.097)	(0.097)	(0.114)	(0.119)
Business	0.146*	0.059	0.120*	-0.055	0.015
	(0.075)	(0.071)	(0.073)	(0.082)	(0.083)
Seasonal labor	0.082	0.052	0.112	0.032	-0.153*
	(0.080)	(0.072)	(0.075)	(0.088)	(0.082)
Remittances	0.156*	0.108	-0.044	0.310****	0.085
	(0.082)	(0.076)	(0.073)	(0.087)	(0.087)
Credit access	0.113	0.183**	0.088	0.210*	-0.056
	(0.093)	(0.091)	(0.091)	(0.108)	(0.101)

Table A2 continued

Explanatory variables	(3) Legume intercropping	(4) Manure	(5) Ridges	(6) Terraces and stone bunds	(7) Vegetative strips
Social group member	-0.008	0.052	-0.189**	0.065	-0.142
	(0.089)	(0.086)	(0.089)	(0.092)	(0.101)
Relatives in village	-0.011	-0.000	-0.015*	0.001	0.008
	(0.010)	(0.009)	(0.009)	(0.011)	(0.010)
Traders in village	0.007	0.007	-0.003	0.024*	0.023*
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Farmer’s group member	0.024	-0.044	0.355***	0.416****	0.098
	(0.119)	(0.120)	(0.112)	(0.119)	(0.130)
Leadership connections	0.038	0.177**	-0.135*	-0.048	0.098
	(0.076)	(0.071)	(0.073)	(0.086)	(0.079)
Relatives outside village	0.018*	-0.012	-0.018**	0.005	0.001
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Traders outside village	0.005	0.001	0.000	0.003	-0.005
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Government support	0.054	-0.011	-0.356****	0.182**	-0.099
	(0.074)	(0.071)	(0.071)	(0.085)	(0.080)
Extension	0.006	0.016*	0.011	-0.007	0.025**
	(0.009)	(0.009)	(0.009)	(0.013)	(0.010)
Water stresses	0.127	0.098	0.307****	0.073	-0.173*
	(0.084)	(0.082)	(0.082)	(0.097)	(0.089)
Pests and diseases	0.283****	0.115*	-0.102	-0.023	0.161**
	(0.073)	(0.069)	(0.070)	(0.083)	(0.080)
Market distance	-0.000	0.001	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Market distance, squared	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Main road passable	0.154	0.105	-0.058	-0.069	0.148
	(0.136)	(0.127)	(0.131)	(0.139)	(0.130)
Farm families in district	0.003	0.004	0.006	-0.009	0.000
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
DPP	0.254***	-0.153	0.211**	-0.092	-0.199**
	(0.097)	(0.096)	(0.090)	(0.106)	(0.101)

Table A2 continued

Explanatory variables	(3) Legume intercropping	(4) Manure	(5) Ridges	(6) Terraces and stone bunds	(7) Vegetative strips
Southern region	0.241**	0.003	-0.310***	0.213*	0.082
	(0.114)	(0.119)	(0.107)	(0.129)	(0.120)
Year	0.189*	0.105	0.495****	-0.077	0.218*
	(0.108)	(0.097)	(0.100)	(0.108)	(0.116)
Constant	-1.829****	-1.016****	-0.581**	-0.815***	-1.555****
	(0.300)	(0.282)	(0.275)	(0.314)	(0.322)

Notes: The number of observations is 1482. Pseudo log-likelihood: -3997.44; Wald chi2(165): 637.36****; Number of draws: 50. Robust SEs, adjusted for 827 household clusters, in parentheses. ****P≤0.001, ***P≤0.01, **P≤0.05, *P≤0.1

Table A3: Multivariate probit model with Mundlak approach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Explanatory variables	Inorganic fertilizer	Improved maize	Legume intercropping	Manure	Ridges	Terraces and stone bunds	Vegetative strips
FISP	1.474****	0.421****	0.010	-0.113	-0.053	-0.117	0.111
	(0.344)	(0.127)	(0.115)	(0.104)	(0.113)	(0.141)	(0.128)
Age	-0.045*	-0.027	-0.023	-0.022	0.012	-0.013	-0.030
	(0.024)	(0.021)	(0.015)	(0.020)	(0.021)	(0.014)	(0.019)
Female head	-0.940**	0.207	0.267	-0.018	-0.072	0.048	0.125
	(0.472)	(0.326)	(0.300)	(0.259)	(0.300)	(0.342)	(0.362)
Education	0.145	-0.023	-0.087	-0.044	0.031	-0.052	0.099
	(0.100)	(0.058)	(0.080)	(0.065)	(0.076)	(0.070)	(0.098)
Adults	-0.069	-0.137**	0.029	0.120**	0.022	-0.020	0.025
	(0.111)	(0.062)	(0.055)	(0.054)	(0.058)	(0.075)	(0.071)
Children	-0.022	0.059	0.021	0.077*	0.007	-0.083	-0.079
	(0.105)	(0.060)	(0.055)	(0.045)	(0.057)	(0.075)	(0.065)
Asset value	0.001	-0.001	-0.002**	-0.001*	-0.000	-0.000	-0.000
	(0.004)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Livestock	-0.054*	-0.014	0.023	0.064**	0.005	-0.030	0.006
	(0.030)	(0.037)	(0.033)	(0.027)	(0.034)	(0.038)	(0.037)
Farm size	0.131*	0.053	0.039	0.153***	0.104**	0.050	0.141**
	(0.075)	(0.052)	(0.052)	(0.053)	(0.051)	(0.057)	(0.058)
Farm size, squared	-0.003	-0.002	-0.003	-0.008**	-0.003	-0.004	-0.008***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Socioeconomic shocks	-0.130	0.008	-0.015	-0.228*	-0.063	0.136	0.400**
	(0.320)	(0.173)	(0.143)	(0.135)	(0.157)	(0.180)	(0.170)
Business	0.088	0.174	0.237**	0.150	0.021	-0.016	0.037
	(0.229)	(0.122)	(0.111)	(0.101)	(0.112)	(0.125)	(0.121)
Seasonal labor	-0.499**	-0.060	0.109	0.187*	0.250**	0.121	-0.071
	(0.216)	(0.118)	(0.123)	(0.099)	(0.120)	(0.139)	(0.128)
Remittances	-0.026	-0.075	0.104	0.116	-0.132	0.262*	0.115
	(0.274)	(0.133)	(0.127)	(0.104)	(0.109)	(0.147)	(0.132)
Credit access	0.627*	-0.079	0.159	0.134	0.135	0.462**	-0.158
	(0.364)	(0.169)	(0.160)	(0.139)	(0.156)	(0.195)	(0.175)

Table A3 continued

Explanatory variables	(1) Inorganic fertilizer	(2) Improved maize	(3) Legume intercropping	(4) Manure	(5) Ridges	(6) Terraces and stone bunds	(7) Vegetative strips
Social group member	0.019	-0.244	0.001	-0.175	-0.404***	0.122	-0.167
	(0.256)	(0.149)	(0.133)	(0.122)	(0.132)	(0.152)	(0.153)
Relatives in village	-0.011	0.019	-0.009	0.008	-0.030**	-0.014	-0.021
	(0.025)	(0.015)	(0.014)	(0.013)	(0.014)	(0.016)	(0.015)
Traders in village	0.014	-0.023	-0.006	-0.008	0.001	0.013	0.049***
	(0.025)	(0.017)	(0.018)	(0.014)	(0.017)	(0.020)	(0.019)
Farmer’s group member	0.227	0.156	0.032	-0.033	0.306	0.213	0.226
	(0.366)	(0.232)	(0.218)	(0.180)	(0.223)	(0.229)	(0.232)
Leadership connections	-0.295	-0.206*	0.181*	0.191**	-0.101	0.075	0.310***
	(0.186)	(0.113)	(0.110)	(0.096)	(0.109)	(0.127)	(0.119)
Relatives outside village	0.091****	0.027*	0.027**	-0.017	-0.013	0.017	0.005
	(0.027)	(0.014)	(0.014)	(0.013)	(0.014)	(0.016)	(0.016)
Traders outside village	-0.003	-0.001	0.010	0.011	0.005	0.006	-0.003
	(0.020)	(0.012)	(0.012)	(0.009)	(0.010)	(0.011)	(0.014)
Government support	-0.014	-0.016	0.016	0.092	-0.333***	0.214	-0.171
	(0.206)	(0.113)	(0.111)	(0.102)	(0.107)	(0.136)	(0.124)
Extension	0.025	-0.018	0.007	0.021	0.005	0.009	0.013
	(0.034)	(0.014)	(0.012)	(0.016)	(0.012)	(0.020)	(0.013)
Water stresses	0.204	-0.340**	-0.037	-0.028	0.147	0.116	-0.256*
	(0.273)	(0.140)	(0.125)	(0.114)	(0.122)	(0.150)	(0.138)
Pests and diseases	0.056	0.033	0.301***	0.058	-0.200*	0.039	0.090
	(0.205)	(0.109)	(0.107)	(0.097)	(0.108)	(0.137)	(0.121)
Market distance	0.009****	-0.001	-0.000	0.002	0.001	0.001	0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Market distance, squared	-0.000***	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Main road passable	-0.165	-0.101	0.172	0.130	-0.045	-0.069	0.167
	(0.232)	(0.138)	(0.139)	(0.128)	(0.132)	(0.139)	(0.130)
Farm families in district	0.126****	-0.025	0.003	-0.002	0.008	-0.009	0.005
	(0.035)	(0.015)	(0.013)	(0.012)	(0.013)	(0.017)	(0.016)

Table A3 continued

Explanatory variables	(1) Inorganic fertilizer	(2) Improved maize	(3) Legume intercropping	(4) Manure	(5) Ridges	(6) Terraces and stone bunds	(7) Vegetative strips
DPP	0.801****	-0.279***	0.240**	-0.162	0.224**	-0.093	-0.207**
	(0.226)	(0.104)	(0.101)	(0.101)	(0.095)	(0.107)	(0.105)
Southern region	-1.487****	0.176	0.203*	-0.044	-0.339***	0.204	0.053
	(0.258)	(0.129)	(0.117)	(0.124)	(0.110)	(0.132)	(0.122)
Year	-1.500****	0.337**	0.207	0.273*	0.612****	-0.150	0.420**
	(0.283)	(0.163)	(0.157)	(0.140)	(0.149)	(0.162)	(0.182)
Constant	0.452	-0.096	-1.911****	-0.995***	-0.752**	-0.753**	-1.492****
	(0.588)	(0.371)	(0.342)	(0.332)	(0.312)	(0.372)	(0.369)
Joint significance of mean of time-varying covariates (chi2)	81.91****	49.20****	22.17	35.98	28.59	21.99	37.09

Notes: The number of observations is 1482. Pseudo log-likelihood: -4806.52; Wald chi2(427): 2541.23****; Number of draws: 50. Robust SEs, adjusted for 827 household clusters, in parentheses. Mundlak approach (inclusion of means of all time-varying covariates) was used for estimation. ****P≤0.001, ***P≤0.01, **P≤0.05, *P≤0.1