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The influence of farm input subsidies on the adoption of natural resource management technologies

Stefan Koppmair, Menale Kassie and Matin Qaim[†]

Farm input subsidies are often criticised on economic and ecological grounds. The promotion of natural resource management (NRM) technologies is widely seen as more sustainable to increase agricultural productivity and food security. 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 analyse 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.

Key words: Africa, fertilizer subsidy, Malawi, small farms, sustainable agriculture, technology adoption.

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

[†] Stefan Koppmair (email: stefan.koppmair@agr.uni-goettingen.de) and Matin Qaim are with the Department of Agricultural Economics and Rural Development, University of Goettingen, Goettingen, Germany. Menale Kassie is with the International Centre of Insect Physiology and Ecology (ICIPE), Nairobi, Kenya. When this research started, Kassie was with the International Maize and Wheat Improvement Center (CIMMYT).

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well-being of smallholders seemed to increase with improved access to subsidised 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. Doubts were raised concerning the Program's profitability, efficiency and financial sustainability (MaSSP 2014). A few studies that evaluated FISP between 2005 and 2010 revealed benefit-cost ratios below one, suggesting that program costs had outweighed program benefits (Jayne *et al.* 2013; Lunduka *et al.* 2013). Returns to subsidised fertilizer were sometimes found lower for poor farm households than for relatively better-off (Ricker-Gilbert and Jayne 2012). Moreover, the program's ecological and social sustainability was questioned (MaSSP 2014). Some nongovernmental organizations (NGOs) maintain that the use of agrochemicals 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 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 harmonise 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. A recent example from Zambia showed that fertilizer subsidies may discourage farmers from adopting fallowing and intercropping practices (Levine 2015; Morgan *et al.* 2017). Empirical evidence on how Malawi's 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) analysed the relationship between fertilizer subsidies and the use of organic manure and observed a positive link. Beyond these relationships, no studies have analysed the effects of input subsidies on the adoption of soil and water conservation practices, such as maize–legume intercropping, soil ridges, terraces or vegetative strips, in Malawi or elsewhere. Here, this research gap is addressed.

In particular, panel data from maize-producing farms, collected in 2011 and 2013, are used to analyse how FISP affects farmers' adoption of different NRM technologies. Two specific research questions are investigated. First, does FISP participation influence the use of NRM technologies, specifically soil and water conservation practices? Second, and more generally, is the adoption of input-intensive technologies compatible with the adoption of NRM practices? To answer these questions, a multivariate probit model that takes explicit account of the correlation between different adoption decisions is developed and estimated.

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 is largely produced for subsistence consumption. An estimated 10–15 per cent of the maize production is sold by farmers, often directly after harvest when smallholder households are in need for cash (Jayne *et al*. 2010; Koppmair *et al*. 2017). Sales are typically made to local traders for use in the domestic market. Maize cultivation in Malawi 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 subsidised 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 (fees were increased more recently). 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 fulfil 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) long-time 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 criticised 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 prompted questions about the program's financial sustainability and have contributed to cuts in the support of other agricultural programs and economic sectors (Arndt *et al*. 2015). International donors are 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 seem 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. A multistage sampling procedure was employed to select districts, villages and households. First, we purposively selected six districts based on their maize production potential, namely Lilongwe, Kasungu, Mchinji, Salima and Ntcheu in the Central, and Balaka in the Southern region of Malawi. In each district, we used lists of the government extension service to randomly select villages proportionate to district size. In total, around 180 villages were thus selected. In each village, two to eight households were randomly selected proportionate to village size, resulting in a total sample of 890 households that were interviewed in the first survey round. 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. The econometric analysis is based on the unbalanced panel. Households with missing data were excluded. The final data set consists of 1,482 observations pooled over the two survey rounds.

3.2 Multivariate probit model of technology adoption

Smallholder farmers have to deal with multiple agricultural production constraints affecting their households' well-being. 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 (Kassie *et al.* 2013, 2015; Wainaina *et al.* 2016). The adoption of multiple technologies can result in complementarities and trade-offs, meaning that some combinations make more sense for farmers than others. A modelling 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).

We use 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:

$$\mathrm{TA}_k^* = \beta_0 + \beta_{1k}\mathrm{FISP} + \beta_{2k}H + \beta_{3k}R + \beta_{4k}T + \varepsilon_k \tag{1}$$

$$\mathrm{TA}_k = \begin{cases} 1 \text{ if } \mathrm{TA}_k^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

where TA_k* denotes a latent variable that can be understood as the expected net benefit from adopting technology k. The model considers seven 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 is FISP, which is a dummy for participation in the subsidy program. For this analysis, the FISP dummy takes a value of one if a farm household received vouchers for the core subsidy package consisting of inorganic fertilizer and improved maize seeds. A few households additionally received vouchers for legume seeds. These households are included in the main analysis, but we exclude them in a robustness check to see whether the additional provision of subsidised legume seeds affects the adoption of some technologies differently. The effect of FISP 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. A range of farm and household characteristics (H), regional characteristics (R) and a year dummy (T) are included as control variables.

The error terms in the MVP jointly follow a multivariate normal distribution with zero conditional mean and variance normalised 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.

It should be mentioned that the MVP coefficient estimates may slightly vary depending on how the order of the equations is specified. We tried estimation using different equation orders, which hardly affected the coefficient estimates. A more general issue when using panel data with observations over time is that serial correlation (i.e. error correlation over time for the same households) and/or heteroscedasticity may occur. For short panels with a large number of observations, serial correlation and heteroscedasticity can both be controlled for by estimating panel-robust standard errors with cluster correction at the household level (Cameron and Trivedi 2010). This approach is used here for all estimated models.

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 nonrandom 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 individual motivation. For instance, among the large number of potential beneficiaries of FISP, farmers 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.

Several studies that analysed the effects of FISP used instrumental variable (IV) approaches to control for unobserved heterogeneity and reduce selection bias (Ricker-Gilbert *et al.* 2011; Karamba 2013; Lunduka *et al.* 2013). However, the identification of reliable instruments can be challenging. Moreover, implementation of IV procedures in a multivariate probit framework is not straightforward. Another way to address the problem of unobserved heterogeneity is to exploit the panel nature of the data and use a fixed effects estimator. Yet, there are two shortcomings of using a standard fixed effects estimator in our context. First, the binary nature of the outcome variables might result in the incidental parameter problem (Greene 2012).

Second, the standard fixed effects procedure would require estimation of single equation models, neglecting possible relationships between different technologies. As an alternative, the MVP model can be modified using an approach proposed by Mundlak (1978), which requires inclusion of the means of all time-varying explanatory variables $\bar{X}$ (including FISP participation, household characteristics and regional characteristics). We use this Mundlak approach and modify the MVP model as follows:

$$\mathrm{TA}_k^* = \beta_0 + \beta_{1k}\mathrm{FISP} + \beta_{2k}H + \beta_{3k}R + \beta_{4k}T + \beta_{5k}\bar{X} + \varepsilon_k \tag{3}$$

Equation (3) controls for unobserved heterogeneity and thus addresses issues of selection bias in the MVP framework (Kassie *et al.* 2015). Note, however, that both the standard fixed effects and the Mundlak approach can only control for unobserved heterogeneity that is time-invariant. As we consider a relatively short time period (2009/10 to 2012/13) and analyse the adoption of various technologies simultaneously, we do not expect significant bias from unobserved time-varying heterogeneity.

4. Results

4.1 Descriptive statistics

Descriptive statistics of explanatory variables used in the regression models are shown in Table 1. Fifty per cent of the sample households had participated in FISP during the seasons covered by the two survey rounds, meaning that they had received at least one voucher for inorganic fertilizer and one for improved 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. The household head is defined as the households' main decision-maker. It is possible that other household members also influence decision-making about technology adoption. In alternative models, we therefore also tried gender of the survey respondent (who was not always the household head), without any major changes in the estimation results. Typical assets – such as farm size and livestock ownership – that were shown to affect technology adoption in many situations were also included in the models. The average farm size of 3.3 acres in the sample is comparable to other recent studies with nationally representative data from Malawi (Ricker-Gilbert *et al.* 2014). 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 (Doss 2006; Noltze *et al.* 2012; Kassie *et al.* 2015). Regional factors include infrastructure conditions, district-level population size and a geographical dummy, among others.

The technology adoption variables considered in this study comprise seven different technologies, namely: (i) inorganic fertilizer; (ii) improved maize

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, ≥age 15 (number)	2.85	1.31
Children	Child household members, ≤age 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
Business	Own business income (dummy)	0.46	0.50
Seasonal labour	Seasonal labour 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
Shocks			
Socio-economic 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
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

Table 1 (*Continued*)

Variable	Description	Mean	SD
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 1,482. 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, reflecting the 2009 election results as obtained from the Malawi Electoral Commission. †1 US Dollar = 364 Malawi Kwacha (MK) (average exchange rate in 2013).

seeds as two input-intensive technologies; (iii) legume intercropping; (iv) manure; (v) soil ridges; (vi) terraces and stone bounds; and (vii) vegetative strips as five NRM technologies. Table 2 presents descriptive statistics for these seven technologies.

The use of inorganic fertilizer and improved maize seeds is widespread in Malawi. Improved maize seeds include hybrids and OPVs with different traits and characteristics adapted to the particular agroecological conditions, such as higher yield potential and/or higher tolerance to drought and crop diseases. 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

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 participants were tested for statistical significance. ***$P \leq 0.01$, **$P \leq 0.05$, *$P \leq 0.1$

of the households. In Malawi, the use of pigeon pea, groundnut, soya bean 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 postindependence 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 run-off and sediment washout. 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 built to generate long-term benefits of soil improvement (Critchley *et al.* 1994). Stone bunds are semi-permeable barriers; excess run-off water can pass through slowly and is filtered, so that sediments are caught. Filtration also promotes levelling off the field behind the stone bunds and the formation of terraces. Relatively high upfront costs for the construction of terraces and stone bunds and pay-offs that only occur over time can discourage adoption by cash-constrained smallholder farmers.

Vegetative strips are used to control run-off 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 nonparticipants. 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, even though all received a voucher for improved seeds. Possibly, some exchange of vouchers between farmers occurs. 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. This is analysed in more detail below.

4.2 MVP model results

4.2.1 Interrelationships between technologies

Before presenting the MVP results themselves, looking at the error term correlation matrix of the model provides an idea of possible interrelationships

Table 3 Correlation matrix for technology adoption equations

	Improved maize	Legume intercropping	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: $\chi^2(21) = 86.57$***						

Notes: The number of observations is 1,482. Robust standard errors are adjusted for 827 household clusters. ***$P \leq 0.01$, **$P \leq 0.05$, *$P \leq 0.1$.

in the adoption of different technologies. The results in Table 3 suggest that the null hypothesis of zero correlation between the error terms needs to be rejected. Most of the correlation coefficients in Table 3 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.

Positive and significant correlation coefficients point at complementarities between technologies. The positive relationship between inorganic fertilizer and improved maize seeds is expected and in line with previous studies (Denning *et al.* 2009; Kassie *et al.* 2013). Improved varieties and hybrids 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 3 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.

4.2.2 FISP participation and technology adoption

We now turn to the results of the MVP model itself, which we use to analyse the influencing factors of farmers' technology adoption. The full estimation results are shown in Tables S1–S4 in the online appendix. Several variables related to human capital, asset ownership, social networks, institutions and agroecological factors have significant effects. We refrain from a detailed discussion of all influencing factors (see Kassie *et al.* 2013, 2015; and 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 4 summarises the influence of FISP participation on technology adoption using four different specifications of the MVP model. (i) The basic model includes FISP participation as a dummy variable without controlling for potential selection bias. This basic model includes FISP participants that – in addition to subsidised fertilizer and improved maize seeds – had also received vouchers for legume seeds. (ii) In the robustness check model, we exclude those FISP participants that had also received vouchers for legume seeds. (iii) The reduced model uses the full sample again, but only includes

Table 4 Effects of FISP participation on technology adoption

	Inorganic fertilizer	Improved maize	Legume intercropping	Manure	Ridges	Terraces and stone bunds	Vegetative strips
Basic model	1.713*** (0.262)	0.688*** (0.083)	0.153** (0.075)	−0.017 (0.073)	−0.031 (0.073)	−0.076 (0.088)	0.172** (0.081)
Log pseudolikelihood = −4920.34; Wald $\chi^2(231)$ = 1025.78***							
Robustness check model	1.693*** (0.271)	0.803*** (0.091)	0.105 (0.079)	−0.014 (0.076)	−0.045 (0.077)	−0.104 (0.092)	0.116 (0.087)
Log pseudolikelihood = −4428.23; Wald χ^2 (231) = 1022.41***							
Reduced model			0.155** (0.075)	−0.018 (0.073)	−0.034 (0.073)	−0.079 (0.088)	0.167** (0.081)
Log pseudolikelihood = −3997.44; Wald $\chi^2(165)$ = 637.36***							
Mundlak model	1.474*** (0.344)	0.421*** (0.127)	0.010 (0.115)	−0.113 (0.104)	−0.053 (0.113)	−0.117 (0.141)	0.111 (0.128)
Joint significance of mean of time-varying covariates (χ^2)	81.91***	49.20***	22.17	35.98	28.59	21.99	37.09
Log pseudolikelihood = −4806.52; Wald χ^2 (427) = 2541.23***							

Notes: The number of observations is 1,482, except for the robustness check model (1,344 observations). In all models, robust standard errors are clustered at the household level. The number of draws (50) was set above the square root of the number of observations to reduce simulation bias (Cappellari and Jenkins 2003). Full estimation results are shown in Tables S1–S4 in the online appendix. ***$P \leq 0.01$, **$P \leq 0.05$, *$P \leq 0.1$.

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. (iv) In the Mundlak model, we use the full sample and control for possible selection bias from unobserved heterogeneity by including the means of all time-varying covariates, as described above.

Results from the basic model in Table 4 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). The basic model suggests significantly positive effects of FISP participation on the adoption of some NRM technologies. In particular, the effects for the use of legume intercropping and vegetative strips are positive and statistically significant. The effect on legume intercropping may be due to subsidised 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). However, this effect may also be driven by some FISP participants also receiving vouchers for legume seeds. Indeed, in the robustness check model, the coefficient of FISP participation in the legume intercropping equation is somewhat smaller and statistically insignificant. In any case, the results underline that subsidies for inorganic fertilizer and improved maize seeds do not prevent farmers from using NRM technologies. The reduced model confirms this finding. However, these results should be interpreted with some caution because of possible selection bias.

The lower part of Table 4 reports the results from the MVP model with the Mundlak approach to control for selection bias. The null hypothesis that all coefficients of the mean of the time-varying covariates are jointly equal to zero is rejected in some of the equations, thus suggesting that unobserved heterogeneity may be an issue. This is controlled for in the Mundlak model. The estimation results confirm the positive effects of FISP on the adoption of inorganic fertilizer and improved maize seeds, but the coefficient estimates are slightly smaller than those in the basic model. This comparison points at an upward bias if unobserved heterogeneity is not corrected for. The estimated effects for the adoption of NRM technologies are also slightly different. However, the coefficient signs remain the same throughout all equations. In none of the equations, the effect of FISP participation is negative and significant. In other words, there is no indication that FISP would have a substantive negative effect on the adoption of NRM technologies among smallholder farmers.

5. Conclusion

The Farm Input Subsidy Program (FISP), which was launched in Malawi in 2005/06, has contributed to bumper harvests and improved well-being 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 criticised for not being economically and ecologically sustainable. In particular, there are doubts that FISP is compatible with NRM technologies that build on improved agronomic practices to raise productivity and conserve soil and water.

In this article, panel data collected from smallholder farm households in Malawi were used to analyse the effect of FISP on the adoption of various technologies, and more generally the compatibility of input-intensive and NRM technologies. Results have shown that FISP participation significantly increases the likelihood of farmers to use inorganic fertilizer and improved maize seeds. This was expected because FISP participants receive vouchers for the purchase of these modern inputs at subsidised rates. For the adoption of NRM technologies, some positive effects of FISP were also found. FISP participation is positively associated with the practice of legume intercropping and the use of vegetative strips. These effects might partly be due to productivity increases in maize resulting from the use of subsidised inputs and a concomitant reallocation of land and other household resources. Vouchers for legume seeds, which some FISP participants received in addition to maize seed and fertilizer subsidies, may also explain the positive effects on intercropping. 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 consider modern inputs and NRM practices as complements, not as substitutes in most cases. Different types of technologies are often adopted in combination.

We conclude that the input subsidies provided to farmers through FISP do not discourage the adoption of NRM practices. These results also hold after controlling for unobserved heterogeneity and possible selection bias in FISP participation. In fact, the use of NRM technologies in Malawi seems to be more common among recipients of input subsidies than among nonrecipients. Hence, the promotion of NRM technologies under FISP is feasible, especially when the focus is broadened beyond maize to also include legumes and other crop species. However, further research is needed 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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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1 Basic multivariate probit model.

Table S2 Robustness check model (multivariate probit model, excluding households that have additionally received voucher for legume seeds).

Table S3 Reduced multivariate probit model (only including equations for NRM technologies).

Table S4 Multivariate probit model with Mundlak approach

Data S1 Data set used for statistical analysis.