DO CHANGES IN MAIZE PRICES AND INPUT PRICES AFFECT SMALLHOLDER FARMERS' SOIL FERTILITY MANAGEMENT DECISIONS? PANEL SURVEY EVIDENCE FROM KENYA

By

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ABSTRACT

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Soil degradation, low cereal yields, and poor yield response to inorganic fertilizer are serious problems in many parts of sub-Saharan Africa (SSA), including Kenya. Soil fertility management (SFM) practices such as maize-legume intercropping and organic fertilizer use, particularly when used jointly with inorganic fertilizer, have the potential to increase yields and yield response to inorganic fertilizer and improve soil health. However, relatively little is known about the drivers of adoption of such SFM practices, including their joint use. Moreover, it is often suggested that African farmers will respond to an increase in the maize price they expect to receive at the next harvest by increasing investment in their soils or that they might alter their use of SFM practices in response to changes in input prices. Yet previous studies largely ignore the role of such prices. Using nationwide household panel survey data from Kenya, we first predict the maize price a household can expect to receive at the upcoming harvest based on observables at the time they make SFM decisions; we then estimate the effects of changes in this predicted maize price and input prices on household adoption decisions for individual SFM practices and combinations thereof. Likely due to multiple market failures, we find that Kenyan smallholders' SFM adoption decisions are largely insensitive to changes in prices; however, there is some evidence that they are more likely to use organic fertilizer and use less inorganic fertilizer per acre when inorganic fertilizer prices rise.

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KEY TO ABBREVIATIONS

APE	Average partial effect
CA	Conservation agriculture
CAN	Calcium ammonium nitrate
CGIAR	Consultative Group for International Agricultural Research
CRE	Correlated random effects
CRU	Climate Research Unit
DAP	Diammonium phosphate
ESA	Eastern and southern Africa
FE	Fixed effects
GDP	Gross domestic product
Kg	Kilogram
Km	Kilometer
Ksh	Kenyan Shilling
NAAIAP	National Accelerated Agricultural Input Access Program
NCPB	National Cereals and Produce Board
POLS	Pooled ordinary least squares
SFM	Soil fertility management
SI	Sustainable intensification
SOM	Soil organic matter
SSA	Sub-Saharan Africa
TAPRA	Tegemeo Agricultural Policy Research and Analysis
TLU	Tropical livestock unit

TOC	Total organic carbon

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1. Introduction

Many nations in sub-Saharan Africa (SSA), including Kenya, are experiencing challenges associated with soil nutrient losses and stagnant agricultural output growth (Eicher 2009; Jayne et al. 1993; Montpellier Panel 2013; NAAIAP 2014). In much of SSA, countries are net importers of food due to many factors, including low agricultural productivity (Drechsel et al. 2001; van lttersum et al. 2016). And while a number of factors undergird the production shortfall, soil fertility depletion has been identified as one of the major drivers (Drechsel et al. 2001; Sanchez et al. 1997; Sanchez and Logan 1992). Moreover, 3.3% of agricultural gross domestic product (GDP) in SSA is lost each year due to soil degradation (Drechsel and Gyiele 1999; Montpellier Panel 2013). Soil fertility depletion has many drivers, including continuous cropping (Brams 1971; Vanlauwe and Giller 2006), lack of nutrient recycling (Bationo et al. 1995; Lal 1995; Marenya and Barrett 2009), and low use of organic and inorganic fertilizers (Oluoch-Kosura, Marenya, and Nzuma, 2004).

Sustainable intensification (SI) has been offered as a potential solution to the issues of declining soil fertility and low agricultural productivity in SSA (Godfray et al. 2010, Montpellier Panel 2013; Pretty et al. 2011, Royal Society 2009). SI is defined as a "process or system where yields are increased without adverse environmental impact and without the cultivation of more land" (Pretty and Bharucha 2014, p. 1578; Royal Society 2009).[1] It does not involve extensification or cultivation of newly cleared or fallowed land. SI is a guiding framework to

[1] Similar definitions have been used by Snapp et al. (2017) and others. Snapp et al. (2017) also integrate social and human condition dimensions into their definition of SI.

inform which agricultural practices or combinations of technologies are sustainable (Garnett and Godfray 2012). SI of maize production is of specific interest in eastern and southern Africa (ESA), where maize is the leading staple food and is grown widely by smallholder farmers. The use of soil fertility management (SFM) practices on maize plots, such as organic and inorganic fertilizers, intercropping or rotating the maize with legumes, and crop residue retention and incorporation, among others, have the potential to contribute to SI in maize-based systems, particularly when inorganic fertilizer and other SFM practices are combined on the same plot (Montpellier Panel 2013; Snapp et al. 2010; Bultena and Hoiberg 1983; Mcdonahe, Lu, and Semalulu 2014). Understanding what factors encourage versus inhibit take-up of these practices by smallholder farmers in SSA is therefore of high policy relevance and importance.

Of particular interest in this study is the role of farmers' expectations about maize producer prices in the SFM adoption process. Economic theory suggests that a farmer's expected maize price is likely to be an important determinant of the farmer's adoption of SFM practices on his/her maize plots.[2] Moreover, several recent reports posit that smallholders might respond to an increase in the maize price they expect to receive at harvest by investing in soil fertility-enhancing practices (Kassie et al. 2015; Montpellier Panel Report 2015; Morris et al. 2007, among others). Yet there is very little empirical evidence to support or contradict this claim. In fact, while there is a growing literature on the drivers of adoption of SFM practices in SSA **(**Kamau et al. 2014, Kassie et al. 2013, Manda et al. 2016, Pretty et al. 2011, Teklewold et al. 2013, among others**)**, very few studies (and none of the relevant studies we identified) include a farmer's expected maize producer price among the potential determinants of adoption of these practices.

[2] Farmers do not know what maize prices will be at harvest time when they are making SFM adoption decisions, so it is their *expectation* of the maize price that is likely to affect behavior.

Of secondary interest in this study is the role of input prices in the adoption process – specifically the prices of inorganic fertilizer and maize and legume seeds, and agricultural wage rates. While economic theory also suggests that input prices are likely to be important determinants of adoption of SFM practices, like maize prices, these prices are infrequently included in the existing SFM literature for SSA. Excluding expected output and input prices may lead to omitted variables bias and inaccurate estimates. A handful of SFM adoption-related studies do include one or more input prices. For example, Kamau et al. (2014) find that an increase in the inorganic fertilizer price is associated with reductions in the likelihood of inorganic fertilizer application, use of erosion control measures, and the use of other soil amendments by Kenyan smallholders. Holden and Lunduka (2012) similarly find that in Malawi, inorganic fertilizer use decreases as its price increases but that organic fertilizer use increases with a rise in the inorganic fertilizer price. Yet most other studies on SFM adoption in SSA omit expected output prices and input prices in their analyses. More research is therefore needed to understand how these prices affect households' adoption decisions.

In this paper, we focus on the case of smallholder farm households in Kenya and use nationwide household panel survey data and econometric methods that control for time invariant heterogeneity to empirically estimate how changes in a household's expected maize price and changes in various input prices affect their adoption of SFM practices that can contribute to SI of maize production. The specific SFM practices analyzed are farmers' use of inorganic fertilizer, organic fertilizer, and maize-legume intercropping, alone and in combination, on their maize plots. Kenya is a relevant case study because, like in much of the region, maize is the main staple food crop and many households are affected by soil degradation. To our knowledge, this is the first study to empirically test whether farmers respond to increases in their expected maize price by adopting more sustainable forms of maize intensification. The study also adds to the thin literature on the role of changes in input prices in African farmers' use of SFM practices.

The remainder of the paper is organized as follows. In section 2, we provide additional information on the SFM practices analyzed in the paper and their contributions to soil fertility. Section 3 summarizes the literature on the drivers of adoption of SFM practices in SSA. The data are discussed in section 4, the conceptual framework is outlined in section 5, the empirical strategy is described in section 6, the results are presented in section 7, and conclusions and policy implications are drawn in section 8.

2. SFM practices analyzed

In this section we discuss, in turn, the three SFM practices with the potential to contribute to SI of maize-based systems that are analyzed in this study (maize-legume intercropping, organic fertilizer, and inorganic fertilizer).[3] Intercropping maize with legumes can benefit the soil and the household in several ways. First, the legumes fix nitrogen into the soil, which adds to the soil's pool of nitrogen. This pool of nitrogen provides the maize with a supply of the element; the other main external source of nitrogen is the application of fertilizer (organic or inorganic). Intercropping maize and legumes reduces the maize's requirements for nitrogen fertilizers (Zentner et al. 2001; Zentner et al. 2004). Maize-legume intercropping has also been

[3] We do not analyze other practices that can contribute to SI in maize based-systems such as rotating maize with legumes, minimum tillage, and crop residue retention and incorporation due to data constraints. For example, information on crop rotation is captured only in the last wave of the panel survey data used here and it only captures crop rotation at the household level, not by plot or field; moreover, it does not capture which crops were rotated. These data suggest that 31.4% of households rotated at least one plot. For minimum tillage, this was again only captured in the last wave of the survey and the practice was used by just 1.3% of households, which is insufficient for meaningful analysis. Regarding crop residue retention, only information on the use of maize stover is captured (not other crop residues) and only in the last wave of the panel survey. The data suggest that 27.4% of households retained some of their maize residues. Retention of legume residues is likely to be equally if not more important for soil fertility but such information is not captured in the surveys.

found to decrease disease, insects (Caswell and Raheja 1972; Power 1988; Skovgård and Päts 1997), and weeds (Steiner 1982) relative to maize monocropping. The legumes can produce a large quantity of plant material, which increases soil fertility and soil organic matter (SOM), especially when it is integrated into the soil after harvest (Liebman and Dyck 1993; Snapp et al. 2010). In addition, the legumes themselves can provide additional nutrients and calories to the farm household (Kassie et al. 2013).

The application of organic fertilizer in the form of animal manure or compost also increases SOM (Vanlauwe 2004). Organic fertilizer can be a complement to inorganic fertilizer, increasing its effectiveness (Juma et al. 1999; Place et al. 2002, Shapiro and Sanders 1998); however, some households use organic fertilizer as a substitute for inorganic fertilizer. Manure also increases the levels of nitrogen, phosphorous, and potassium in the soil, all of which are important to the development of plants (Gutser et al 2005). Inorganic fertilizer adds these elements to the soil for plant use as well (Marenya and Barrett 2007; Sanchez et al.1997). However, inorganic fertilizer application alone can damage soils in the following ways when not used appropriately: water pollution, destruction of micro-organisms, damage to plant tissues, and soil acidification (Schroder et al. 2011, Lungu and Dynoodt 2008, Savci 2012). High soil acidity reduces crop response to inorganic fertilizers (Wong et al. 1995). Soil acidification is of particular concern in Kenya due to the continuous use of inorganic fertilizer. In fact, a recent report suggests that nearly every county in Kenya has soil acidity challenges, with average pH levels below the ideal level for maize production (NAAIAP 2014).[4] One soil additive that that can reduce soil acidity is lime (Haynes 1984), however no households in our sample report using

[4] NAAIAP (2014) summarizes the results of soil samples collected throughout Kenya and provides county-specific soil amendment recommendations for maize cultivation. It considers a pH of 5.5 or higher and total organic carbon (TOC) levels of 2.7% or higher to be the ideal for maize production (NAAIAP 2014). TOC is one element of SOM. The equation to convert TOC to SOM is SOM(%) = 1.2 * TOC(%)

lime on their maize fields. This suggests that households either do not have access to lime, that it is not profitable to use, or that they are unaware of its possible benefits. In addition to lime, the application of cattle manure can also counter soil acidification (Whalen et al. 2000).

The potential of these SFM practices to help build SOM is important in the Kenyan context because SOM levels are low in much of country. In fact, average SOM levels are below the ideal level for maize in all counties in the country (NAAIAP 2014). SOM is a relatively slowly-changing characteristic of the soil. This means that it takes time to transform a poor quality, low SOM soil into a higher quality, high SOM soil. In many cases, this process takes several years at a minimum (Bot and Benites 2005). SOM is directly linked to the productivity of plants (Bauer and Black, 1994). SOM also regulates the amount of water that is retained in the soil (Juma 1999) and regulates the release of nutrients into the soil for plant use (Bot and Benites 2005). The application of SFM practices over one season may improve yields, but it is over multiple seasons that the majority of benefits are typically observed, particularly for maize-legume intercropping and organic fertilizer use (Pretty et al. 2011, Mungai et al. 2016). For example, Pretty et al. (2011) examine the benefits of conservation agriculture (CA), which includes some of our SFM practices, over a minimum of three years and found that more benefits are derived the longer the practices are used. We expect that the majority of improvements to yield and soil fertility from the use of organic fertilizer and intercropping of maize and legumes will accrue after these techniques are used for multiple seasons.[5]

[5] Unfortunately, the data used here do not track plots over time so we are unable to empirically model these dynamics.

3. Drivers of adoption of SFM practices in SSA

There have been a number of empirical studies on the drivers of adoption of SFM practices in SSA (Kamau et al. 2014; Manda et al. 2016; Teklewold et al. 2013; among others), and most utilize a random utility model (Kassie et al. 2015; Manda, Smale, Mutua 2016; Marenya and Barrett 2007; Teklewold, Kassie, and Shiferaw 2013; among others). Although random utility models are common in the literature, they are very general and do not provide much insight on the specific variables that are likely to drive adoption decisions and thus that should be included in one's empirical specification. Moreover (and perhaps related to the previous point), very few studies in this literature consider the role of input prices in adoption, and, to our knowledge, no previous studies on SFM adoption in SSA consider the role of expected output prices.[6] Below, we improve upon much of the previous work in this literature by grounding our empirical model in a more specific theoretical framework and by explicitly considering the roles of input and expected output prices.

Previous studies do, however, point to three key factors that consistently affect SFM adoption decisions: labor availability, land tenure security, and the gender of the household head. Given that many SFM practices are labor-intensive, labor availability is an important determinant of adoption, particularly when there are labor market imperfections (Feder, Just, and Zilberman 1985). The positive effect of family labor availability on adoption is born out in many empirical studies on the use of animal manure, other non-chemical fertilizer soil amendments, and combinations of SFM practices (Kamau, Smale, and Mutua 2014; Kassie et al. 2013; Kassie et al. 2015; Manda et al. 2016; Marenya and Barrett 2007; Teklewold et al. 2013). Findings by Koppmair, Kassie, and Qaim (2016) are more nuanced and indicate that the number of prime age

[6] See the introduction for a brief discussion of the results of the relevant studies that *do* include input prices.

adults in the household is negatively associated with manure application, while seasonal hired labor is positively associated with manure use and negatively associated with chemical fertilizer use. Kamau, Smale, and Mutua (2014) find a negative relationship between the number of prime age adults in the household and the application of inorganic fertilizer to both maize and non-maize plots.

Land tenure security is also likely to be an important determinant of adoption of SFM practices, particularly those that take time to yield improvements in soil fertility and crop productivity (Feder, Just, and Zilberman 1985). Indeed, empirical findings suggest that use of animal manure and the retention of crop residues are positively correlated with more secure land tenure (Kassie et al. 2013; Kassie et al. 2015; Manda et al. 2016; Ndiritu, Kassie, and Shiferaw 2014). Silberg et al. (2017) find the same for maize-legume intercropping in Malawi. In contrast, some studies suggest that inorganic fertilizer use, which would be expected to yield benefits in the season in which it is applied (especially for nitrogenous fertilizers), increases with greater tenure *in*security (e.g., Asfaw, Manuela, and Lipper 2015; Kassie et al. 2013; Kassie and Holden 2007). However, several other studies find the opposite relationship (Kamau, Smale, and Mutua 2014; Kassie et al. 2015; Koppmair, Kassie, and Qaim 2016). The role of land tenure security has also been considered in the context of adoption of multiple SFM practices. The results suggest that more secure property rights are associated with a higher likelihood of adoption of a combination of SFM practices (Kassie et al. 2013; Manda et al. 2016; Teklewold, Kassie, and Shiferaw 2013).

The third common determinant of SFM adoption highlighted in the literature is the gender of the household head. Most previous studies suggest that male-headed households are more likely than female-headed households to adopt and use SFM practices such as crop residue retention (Manda et al. 2016), maize-legume rotation (Manda et al. 2016), and inorganic fertilizer (Kassie et al. 2015; Marenya and Barrett 2007; Marenya and Barrett 2009; Murendo et al. 2016). However, Kassie et al. (2015) find that in the specific case of maize-legume intercropping in Tanzania, adoption is more likely under female household headship than male household headship.

Work by Berazneva, Conrad, and Guerena (2014) is also relevant for our study. They develop a dynamic bioeconomic model of soil carbon at the household level in western Kenya. The practices that are examined in detail include the application of inorganic fertilizer and crop residue retention. They find that it is possible to double maize yields and create large stocks of soil carbon by incorporating both of these practices over time. However, transitioning the soil from its current fertility level to a higher level requires intensive investment in chemical and organic inputs that is not currently seen in Kenya. These results are sensitive to the discount rate that is used, with higher discount rates resulting in lower investments. While related to our study, Berazneva, Conrad, and Guerena (2014) do not consider maize-legume intercropping or animal manure application as we do here, nor do they consider several of the determinants included in our models; moreover, their study is mainly theoretical whereas our study is mainly empirical.

4. Data

The data used in our analysis come primarily from the Tegemeo Institute of Agricultural Policy and Development's Tegemeo Agricultural Policy Research and Analysis (TAPRA) household panel surveys.[7] The TAPRA data are a five-wave panel, collected in 1997, 2000,

[7] The Tegemeo Institute is headquartered in Nairobi, Kenya and is part of the Division of Research and Extension of Egerton University.

2004, 2007, and 2010; however, our analysis uses only the final two waves because some important variables for the analysis were not collected in earlier waves of the survey.

The TAPRA surveys aimed to provide nationwide data on agricultural household activities, such as plot level input use and management practices, plot level harvest data, agricultural input and output prices, and household assets, in addition to other household information. The first (1997) wave of the survey covered 120 villages in 24 districts across the country (Argwings-Kodhek et al. 1998), and a total of 1,540 rural agricultural households were interviewed that year. After 2000 however, households in two districts (Turkana and Garissa) were not interviewed due to these districts primarily having pastoral agricultural activity and low maize production. Of the original 1,540 households, 1,500 were in districts that were targeted for re-interview after the 2000 wave. Of these 1,500 households, 1,308 are present in the fourth (2007) wave and 1,275 in the final (2010) wave.

The starting point for our analytical sample is the 1,275 panel household observations for both the 2007 and 2010 TAPRA surveys (2,550 household-year observations). Almost all of these households cultivate maize; however, there are 35 (21 in 2007 and 14 in 2010) households that do not. We have removed these households from our analytical sample. Further narrowing of the analytical sample is done by restricting the definition of a maize plot, as our focus here is on farmers' use of SFM practices on their maize plots. We follow Sheahan et al. (2013) and define a maize plot as one that: (1) has maize cultivated on it; (2) has no more than six distinct crops grown on the plot; and (3) where maize is not intercropped with a cash crop (the assumption here being that the cash crop, not the maize, is the main crop on the plot). This narrows our analytical sample down to 1,296 households-year observations with 648 in 2007 and 648 in 2010 for the balanced panel. These households cultivate a total of 1,667 maize plots (as defined above), with 862 in 2007 and 805 in 2010.

In addition to the TAPRA data, we use rainfall data from the CGIAR Climate Research Unit (CRU) (Hijmans et al. 2005). These data are at a ten-square kilometer (km) resolution and are merged with the TAPRA data at the village level.

We also include as control variables in an auxiliary regression (discussed below) variables related to the quantity of maize purchased by and the maize price paid to farmers by the National Cereals and Produce Board (NCPB), Kenya's maize marketing board. These data are at the division level and were obtained from the NCPB. Also included in this auxiliary regression are regional wholesale maize prices that were collected by the Tegemeo Institute.

Regarding data on the SFM practices analyzed here (inorganic fertilizer, organic fertilizer, and maize-legume intercropping, as well as their combinations), the TAPRA survey includes animal manure and compost as individual practices; however, we group these together as "organic fertilizer". Of the 588 total maize plots with organic fertilizer applied in our analytical sample, 563 were manure and 28 were compost; three plots had both manure and compost applied. At the household level, 508 (39.2%) of the 1296 total households used manure on maize, and 24 (1.9%) used compost. Overall, organic fertilizer is applied on 35.3% of the maize plots and used by 40.7% of the households in the analytical sample. For the practice of maize-legume intercropping, the legume crops that are intercropped with maize by sample farmers are: common beans, cowpeas, pigeon peas, groundnuts, green grams, and soy beans. A breakdown of their individual prevalence as an intercropped legume with maize is shown in table 1. Common bean is by far the legume that is most commonly included in maize-legume intercrops in Kenya (at 97.1% of all maize-legume intercropped plots). Cowpeas are a distant second at 9.6% of maize-legume intercropped plots. Overall, 74.6% of maize plots in the analytical sample are maize-legume intercrops, while 83.1% of households use the practice. For the use of inorganic fertilizer, the survey instrument captures many different types and blends of inorganic fertilizer, all of which are considered inorganic fertilizer in our analysis. Inorganic fertilizer is applied to 82.3% of maize plots and used by 85.0% of the households in the sample.[8]

Table 1: Maize-legume intercrops in Kenya by legume type (pooled 2007 & 2010 sample)

Legume	Number of maize-legume intercropped plots in sample	Percent of maize-legume intercropped plots in sample (N=1,243)	Percent of all maize plots in sample (N=1,667)
Common bean	1,207	97.1%	72.4%
Cowpeas	119	9.6%	7.1%
Pigeon pea	23	1.9%	1.4%
Ground nuts	25	2.0%	1.5%
Green grams	12	1.0%	0.7%
Soy beans	15	1.2%	0.9%

Notes: Some maize-legume intercropped plots include more than one legume. Figures are based on all maize-legume intercropped plots (N=1,243) and all maize plots (N=1,667) cultivated by balanced panel maize-growing households in the 2007 and 2010 waves of the TAPRA household panel survey.
Source: Author's calculations. See text for details on data source.

In this paper, in addition to separately analyzing the determinants of Kenyan smallholder farm households' use of each of the three SFM practices, we also analyze their use of combinations of these practices. There are eight possible combinations of these practice (see table 2). We follow Kim, Mason, and Snapp (2017) and categorize the different combinations of SFM practices by the extent to which they can contribute to sustainable intensification in maize-based systems; we refer to these as "SI categories". Per Kim, Mason, and Snapp, organic fertilizer and maize-legume intercropping are each considered a "sustainable" practice and

[8] The two most commonly used inorganic fertilizers in our data are diammonium phosphate (DAP) and calcium ammonium nitrate (CAN). DAP is applied to 69.9% of maize plots, while CAN is applied to 32.3%; 38.4% of maize plots have both applied. DAP is commonly used as basal dressing and CAN as top dressing in Kenya, which is why there is significant overlap in their application.

inorganic fertilizer is considered an “intensification” practice. The combined use of at least one sustainable practice plus inorganic fertilizer on the same plot is considered to be a form of maize “sustainable intensification” (SI). We go beyond Kim, Mason, and Snapp (2017) and distinguish between “weak SI” and “strong SI” combinations of SFM practices, where the former is inorganic fertilizer combined with *either* organic fertilizer *or* maize-legume intercropping, and the latter is the combination of *all three* practices. Organic fertilizer and maize-legume intercropping are classified as sustainable practices because they can be done individually over time with fewer negative effects on soil health relative to maize monocropping or maize plots without organic fertilizer (Dahmardeh et al. 2010). Indeed, when applied appropriately, these practices can contribute to increased soil fertility (Snaginga and Woomer 2009). On the other hand, the application of inorganic fertilizer alone over time without any sustainable practice can result in soil acidification. This is particularly a problem with the application of DAP and CAN fertilizers due to their high content of ammonia. However, when inorganic fertilizer is combined with a sustainable practice, soil health may be maintained or even improve (Chand, Anwar, and Patra 2006; Chen 2006; Dutta et al. 2003; Kaur, Kapoor, and Gupta, 2005; Snaginga and Woomer 2009).

Table 2 shows the prevalence of the various combinations of SFM practices (and associated SI categories) at the maize plot level. Very few maize plots (2.2%) are monocropped and have no form of fertilizer applied. Weak SI is the most common SI category in our sample, with 50.5% of all maize plots falling in this category. Strong SI is the second most common category at 18.2% of all maize plots, followed by Sustainable at 15.5% and Intensification at 13.6%.

The analysis in this paper is conducted at the household level, not the plot level, due to a lack of adequate plot-level control variables. (We have data on the SFM practices used on the plot and the plot size but no data on other plot-level characteristics.) One of the models we seek to estimate (as discussed further below) is a multinomial logit model of the household's SI category; we use the plot-level SI category information to construct a household-level SI category variable. We determine a household's SI category based on the proportion of maize area it devotes to each SI category; the household-level SI category is then the SI category that accounts for the highest share of total maize area. Note that 964 households in our analytical sample of 1,296 households (74.4%) have only one maize plot (so their plot-level and household-level SI categories are automatically the same), while 332 (25.6%) have two or more maize plots. In the case of a tie between two SI categories as having the largest proportion of a household's maize area, we follow Kim, Mason, and Snapp (2017) and assign the household to the SI category with the higher "SI ranking"; this occurred in 196 cases across the two surveys. See table 3 for the SI rankings, which are based on Kim, Mason, and Snapp (2017); this is the only way in which the SI rankings are used in this paper. Kim, Mason, and Snapp (2017) base the SI rankings on the degree to which each SI category is likely to contribute to SI in maize-based systems. Finally, due to the low percentage of households in the "None" SI category (1.5%), we exclude the 19 households that fall into this category from the analysis. Of the remaining households in the analytical sample, 11.7% are in the Intensification category, 13.3% in Sustainable, 54.4% in Weak SI, and 20.6% in Strong SI (table 3).

Table 2: SFM practice combinations on maize plots, SI category designation, and prevalence in Kenya

Case	Inorganic fertilizer?	Organic fertilizer?	Maize-legume intercrop?	Number of maize plots	Percent of maize plots	SI category	Percent of maize plots by SI category (excluding the "None" category)
1	No	No	No	37	2.2%	None	N/A
2	Yes	No	No	226	13.6%	Intensification	13.9%
3	No	Yes	No	52	3.1%	Sustainable	15.8%
4	No	No	Yes	83	5.0%		
5	No	Yes	Yes	123	7.4%		
6	Yes	Yes	No	109	6.5%	Weak SI	51.7%
7	Yes	No	Yes	733	44.0%		
8	Yes	Yes	Yes	304	18.2%	Strong SI	18.7%
Total number of maize plots with:							
Maize-legume intercropping				1,243	74.6%		
Inorganic fertilizer				1,372	82.3%		
Organic fertilizer				588	35.3%		

Notes: Figures are based on all maize plots cultivated by balanced panel maize-growing households in the 2007 and 2010 waves of the TAPRA household panel survey. N=1,667 maize plots, of which 862 are for 2007 and 805 are for 2010.
Source: Author's calculations. See text for details on data sources.

Table 3: SI categories, rankings, and prevalence among maize-growing households in Kenya

SI category	SI ranking	Number of household-year observations	Percent of household-year observations (all SI categories)	Percent of household-year observations (excluding the "None" SI category)
None	0	19	1.5%	N/A
Intensification	1	149	11.5%	11.7%
Sustainable	2	170	13.1%	13.3%
Weak SI	3	695	53.6%	54.4%
Strong SI	4	263	20.3%	20.6%
Total number of household-year observations using:				
Maize-legume intercropping		1,077	83.1%	N/A
Inorganic fertilizer		1,101	85.0%	N/A
Organic fertilizer		528	40.7%	N/A

Notes: Figures are based on the balanced panel of households with maize plots in the 2007 and 2010 waves of the TAPRA household panel survey. N=1,296 maize-growing household-year observations (648 in 2007 and 648 in 2010).
Source: Author's calculations. See text for details on data sources.

5. Conceptual framework

To represent the household's decision-making process, we begin with an agricultural household model. Per the seminal work of Singh, Squire, and Strauss (1986), when agricultural households face complete and perfectly competitive markets (or if only *one* market is missing or imperfect), and the household is the appropriate unit of analysis, then a household's production decisions are separable from its consumption decisions. Multiple missing or imperfect markets are likely in the rural Kenyan context (especially for organic fertilizer, credit, insurance, land,

and labor), so we assume that separability does not hold. As a result, the household's production-related decisions (e.g., agricultural technology adoption, input demand, and output supply decisions) are intertwined with its consumption decisions.

Our conceptual framework extends the non-separable agricultural household model utilized by Kamau, Smale, and Mutua (2014), who studied Kenyan farmers' inorganic fertilizer, erosion control, and soil amendment adoption decisions. In this framework, a household's objective is to maximize its expected utility, which is derived from consumption of agricultural goods (some of which may be produced by the household), market-purchased goods, and leisure, subject to the household's full income and production function constraints, and constraints related to the multiple market failures. Under these circumstances, the household's demand for SFM practices, $\boldsymbol{SFM}^{*}$ (in our case inorganic fertilizer, organic fertilizer, maize-legume intercropping, or a given SI category), is:

(1) $\boldsymbol{SFM}^{*} = \boldsymbol{SFM}^{*}\ (A, L, O, \boldsymbol{w}, \boldsymbol{P^{e}}, \boldsymbol{Z_{h}}, \boldsymbol{Z_{m}}, \boldsymbol{S})$

where A is the household's landholding size; L is the household's labor endowment; O is off-farm income; $\boldsymbol{w}$ is a vector of agricultural input prices; $\boldsymbol{P^{e}}$ is a vector of expected crop prices; $\boldsymbol{Z_{h}}$ and $\boldsymbol{Z_{m}}$ are, respectively, vectors of other household and market characteristics that affect the household's production and/or consumption decisions; and $\boldsymbol{S}$ is a vector of variables related to agro-ecological conditions.

Expected crop prices are utilized because households make their SFM adoption decisions early in the cropping season, well before harvest-time prices are realized. Of particular interest in this study is how a farmer's expected maize price influences adoption decisions. We therefore decompose the vector $\boldsymbol{P^{e}}$ into two components: the expected maize price ($P^{m,e}$) and a vector of other expected crop prices ($\boldsymbol{P^{o,e}}$). In this paper, we are also interested in how a change in one of the input prices (w) faced by a household affects its SFM adoption decisions, *ceteris paribus*.

Note that this conceptual model is static and ignores soil fertility and other dynamics over time, as we are unable to empirically model these dynamics due to data constraints. By ignoring the dynamics, we are essentially assuming that farmers have high discount rates.

6. Empirical strategy

An empirical model corresponding to equation 1 is what we seek to estimate for the various SFM practices (and combinations thereof). However, because expected crop prices are not observable, we need to make some additional assumptions about farmers' price expectations in order to specify our empirical models. In this study, the main expected crop price of interest is that for maize. To model a farmer's expected maize price, we follow Mason et al. (2015) and Mather and Jayne (2011) who previously studied Zambian and Kenyan smallholders' maize price expectations and use a quasi-rational expectations-like approach (Nerlove and Fornari 1998). In this approach (the empirics of which are discussed in detail below), a farmer's expected maize price is modeled as the *predicted* price they receive at harvest time as a function of information plausibly known to the farmer at the time that SFM decisions are made. We prefer this approach to assuming naïve expectations for the maize price because it is likely that both the past year's price and other factors affect household's price expectations; a naïve expectations approach would ignore these other factors. Assuming that a farmer's expected maize price at the upcoming harvest is equal to last season's harvest price would also limit our ability to investigate the determinants of a household's expected maize price, which is critical to understanding how smallholder farmers think about their economic environment. However, as robustness checks, we estimate models in which we assume naïve expectations for the maize price and another set of models in which we assume perfect foresight for the expected maize price. The perfect foresight assumption is that the household knows the price they are to receive at harvest at the time SFM decisions are made. Expected prices for other crops are not of central interest here and so, for tractability, we assume naïve expectations for farmers' expectations of other crop prices.

Our estimation procedure consists of two main steps: (1) estimating each household's expected maize price; and (2) estimating the effects of the expected maize price (and other factors) on households' maize-related SFM adoption and SI category decisions. This analysis is conducted at the household level and focuses only on maize growers.

6.1. Step 1: Estimating the household's expected maize price

To estimate a household's expected maize price, we begin by estimating the following equation:

$$(2)\quad P_{i,t}^{m} = \beta_0 + \boldsymbol{w}_{\boldsymbol{v,t}}\boldsymbol{\beta_1} + \beta_2 P_{r,t-1}^{m} + \boldsymbol{NCPB}_{\boldsymbol{d,t-1}}\boldsymbol{\beta_3} + \boldsymbol{Z}_{\boldsymbol{h,i,t}}\boldsymbol{\beta_4} + \boldsymbol{Z}_{\boldsymbol{m,v,t}}\boldsymbol{\beta_5} + \boldsymbol{S}_{\boldsymbol{v,t}}\boldsymbol{\beta_6} + c_i + \varepsilon_{i,t}$$

In equation 2, P_{it}^{m} is household *i*'s observed maize sale price at harvest time in agricultural year t;[9] the β's are parameters to be estimated; c_i is time-constant unobserved heterogeneity; and $\varepsilon_{i,t}$ is the time-varying error term for the household. *d* indexes the division, *r* indexes the region, and *v* indexes the village. All right hand-side variables in equation 2 (excluding the error terms) are assumed to be known by the household at the time SFM decisions are made and may affect the maize price they expect to receive at the upcoming harvest. $\boldsymbol{w}$ is a vector of input prices in agricultural year *t*. $P_{r,t-1}^{m}$ is the average wholesale maize price in the household's region during

[9] Our analysis of SFM adoption decisions focuses only on the primary growing season and ignores the minor growing season in Kenya, so the maize price on the left-hand side of equation 2 is for the main growing season.

the last plentiful season, which we define as the three months after the last main season harvest. $\boldsymbol{Z_h}$ and $\boldsymbol{Z_m}$ are vectors of household characteristics and non-price market factors, respectively. See table 4 for details on the specific variables included in $\boldsymbol{w}$ and the two $\boldsymbol{Z}$ vectors, as well as summary statistics for all variables included in equation 2. $\boldsymbol{S_{v,t}}$ captures lagged rainfall conditions (6-year moving averages in the household's village) to proxy for the household's anticipated weather conditions in season *t*; it also includes a vector of agro-ecological zone indicator variables and a variable controlling for rain stress. Rain stress is defined as the fraction of 20 day periods in the main season with less than 40 mm of rainfall. The vector $\boldsymbol{NCPB}_{d,t-1}$ contains the lagged (previous harvest) division-level quantity of maize purchased by the NCPB and the lagged NCPB pan-territorial maize purchase price adjusted for transportation costs from the household's village to the nearest NCPB depot. Recall that the NCPB is Kenya's maize marketing board; it buys maize from farmers and traders at a pan-territorial price at its depots throughout Kenya. We include these NCPB variables in the model because prior studies have shown that maize marketing boards' administratively-determined prices or maize marketing activities can affect maize market prices and/or smallholder farmers' maize price expectations. For example, results in Jayne, Myers and Nyoro (2008) suggest that the NCPB's purchases and sales of maize at non-market prices boosted wholesale maize prices in Kenya by 20% over the period 1995-2004, and decreased the variability (coefficient of variation) of these prices by over 35%. Mason and Myers (2013) find similar effects for the Food Reserve Agency in Zambia, which is also a maize marketing board. Additionally, Mather and Jayne (2011) and Mason et al. (2015) similarly find that marketing board purchase prices in the previous year were significant determinants of a household's maize price at the next harvest, while the marketing board's purchase quantity was not influential.

Table 4: Summary statistics of variables included in the maize price regression

Variables	Mean	Std. Dev
Dependent variable		
Maize price received by household (real 2010 Ksh/kg)	19.32	3.84
Explanatory variables		
Maize seed price (real 2010 Ksh/kg, village median)	68.18	36.49
DAP fertilizer price (real 2010 Ksh/kg, village median)	57.26	5.14
Farm wage (real 2010 Ksh/hour, village median)	20.68	5.56
Land rental rate (real 2010 Ksh/acre/year, village median)	4351.36	1687.43
Plentiful season average wholesale price of maize (real 2010 Ksh/kg)	28.05	4.75
Farmgate NCPB maize price (t-1, real 2010 Ksh/kg)	14.81	6.82
NCPB purchases of maize at division level (MT, t-1)	26.92	87.33
=1 if female headed	0.20	0.40
Age of the HH head (years)	58.47	13.00
=1 if lower primary was the highest level of education	0.08	0.27
=1 if upper primary was the highest level of education	0.43	0.50
=1 if secondary was the highest level of education	0.24	0.43
=1 if post-secondary was the highest level of education	0.08	0.27
Number of prime age adults (age 15 to 59)	3.28	1.83
Total landholdings owned as of prior survey (acres)	8.56	19.56
Value of productive assets as of prior survey (1000s of real 2010 Ksh)	0.30	3.18
Tropical Livestock Units owned as of one year ago	4.28	8.03
=1 if the household had a car, truck, or motorcycle in the prior survey	0.05	0.23
=1 if the HH had a cart in the prior survey	0.05	0.21
=1 if the HH had a bike in the prior survey	0.52	0.50
=1 if the HH had stores in the prior survey	0.44	0.50
Km to the nearest market place for farm produce	4.42	4.24
Km to the nearest motorable road	0.45	0.91
Km to the nearest fertilizer seller	3.45	3.26
Km to the nearest place to get extension advice	5.10	4.84
=1 if year is 2010	0.48	0.50
Average rain in prior six main cropping seasons (mm)	576.03	179.31
Average rain stress in prior six main cropping seasons	0.28	0.20

Source: Author's calculations. See text for details on data sources.
Notes: N=615. Tropical Livestock Units are defined as: cattle = 0.7, sheep & goats = 0.1, pigs = 0.2, chickens = 0.01, rabbits = 0.01. Agro-ecological zone dummies are omitted from this table but are included in the regression. In cases where values as of the previous survey are used, it is because the survey instrument captured values as of the time of interview for those questions, which would have been after SFM decisions were made. We use values as of the previous survey wave to ensure that these values are pre-determined at the time that SFM decisions were made.

Equation 3 is a simplified version of equation 2 to facilitate the following discussion.

(3) $p_{i,t}^{m} = \boldsymbol{\Omega}_{\boldsymbol{g},\boldsymbol{t}-\mathbf{1}}\boldsymbol{\beta} + c_i + \varepsilon_{i,t}$

In equation 3, $\boldsymbol{\beta}$ is the vector of parameters to be estimated and $\boldsymbol{\Omega}_{\boldsymbol{g},\boldsymbol{t}-\mathbf{1}}$ is a composite vector of all of the explanatory variables in equation 2, where g is the level at which the data are defined (i.e., $d, v, r,$ and i) and the *t-1* subscript here should be interpreted as signifying that all variables are realized at or before the time SFM decisions are made. To estimate equation 3 while controlling for potential correlation between c_i and the observed covariates, we use Mundlak-Chamberlain correlated random effects pooled ordinary least squares (CRE-POLS). The data used to estimate equation 3 are from sample households that sold maize because it is only for these households that we observe the maize price received at harvest time. In order to obtain consistent estimates via the CRE approach, we must make the assumption of strict exogeneity of the covariates in the maize price regression ($\boldsymbol{\Omega}_{\boldsymbol{g},\boldsymbol{t}-\mathbf{1}}$) conditional on the unobserved heterogeneity (c_i). That is $\mathrm{E}\left(\varepsilon_{i,t} \middle| \boldsymbol{\Omega}_{\boldsymbol{g},\boldsymbol{t}-\mathbf{1}}, c_i\right) = 0, t = 1,2, \ldots T$, meaning that the observed covariates at any time t are not correlated with the error term $\varepsilon_{i,t}$ at any time t. In addition to strict exogeneity we must assume that $c_i = \psi + \bar{\boldsymbol{\Omega}}_{\boldsymbol{g}}\boldsymbol{\xi} + a_i$ and $c_i | \boldsymbol{\Omega}_{\boldsymbol{g}} \sim Normal\left(\psi + \bar{\boldsymbol{\Omega}}_{\boldsymbol{g}}\boldsymbol{\xi}, \sigma_a^2\right)$, where $\bar{\boldsymbol{\Omega}}_{\boldsymbol{g}}$ is the average of the $\boldsymbol{\Omega}_{\boldsymbol{g}}$ variables for each household across the two survey years and σ_a^2 is the variance of a_i. Under these assumptions, we can control for c_i by including the means of the explanatory variables as additional regressors in equation 3 (Chamberlain 1984; Mundlak 1978; Wooldridge 2010). One benefit to using CRE over fixed effects (FE), an alternative approach to control for time constant unobserved heterogeneity (c_i), is that CRE allows us to use all observations of maize sales, whereas FE would only use observations for households that sold maize in both of our panel survey years (2007 and 2010).

Once equation 3 is estimated, we can use it to generate a predicted maize price $\widehat{p_{\iota,t}^{m}}$ for *all* households in the analytical sample, not just those that sold maize (see equation 4). This is possible because the values of the observed explanatory variables on the right-hand side of equations 2 through 4 are known for all households (both maize sellers and non-sellers). The predicted price is then used as a proxy for the household's expected maize price in the SFM adoption regressions. Again, this is the approach used by Mason et al. (2015) and Mather and Jayne (2011) and is an adaptation of the quasi-rational expectations approach of Nerlove and Fornari (1998).

$$(4)\quad \widehat{p_{\iota,t}^{m}} = \boldsymbol{\Omega}_{\boldsymbol{g,t-1}}\widehat{\boldsymbol{\beta}} + \widehat{c_{\iota}}$$

A challenge that we face in estimating equation 3, however, is that only 47.5% of households in our sample sold maize. (Recall that all households in the analytical sample grow maize.) Our approach leads to the possibility that the estimates of the parameters in equation 3 and used in equation 4 could be biased if the households that sold maize are non-randomly different in unobserved, time-varying ways from those that did not sell maize. We therefore test for selection bias due to incidental truncation following the procedure outlined in Wooldridge (2002, p. 572). (Incidental truncation here refers to the fact that we only observe the maize price received for maize sellers.) This test involves estimating a CRE Tobit regression in which the dependent variable is the quantity of maize sold by the household (which is a positive value for sellers and zero for non-sellers) and the explanatory variables are the same as in the main maize price regression (equation 3). The residuals from this regression (call them $\widehat{u_{\iota,t}}$) are then included as an additional regressor in the maize price regression as shown in equation 5. A t-test of the residuals tests the null hypothesis of no selection bias against the alternative of selection bias. Results of this test suggest that we fail to reject the null of no selection bias in our maize price expectation regression (P=0.86).

(5) $p_{i,t}^{m} = \boldsymbol{\Omega_{g,t-1}\beta} + \alpha\ \widehat{u_{i,t}} + c_i + \varepsilon_{i,t}$

6.2. Step 2: Estimating the effects of the expected maize price and other factors on SFM adoption

To estimate the effects of (our proxy for) the expected maize price and other factors on maize growers' SFM adoption decisions, we bring equation 1 to the data and specify the following general empirical model:

(6) $SFM_{i,t} = \gamma_1\widehat{P_{i,t}^{m}} + \gamma_2 P_{i,t-1}^{o} + \gamma_3 A_{i,t} + \gamma_4 L_{i,t} + \gamma_5 O_{i,t} + \boldsymbol{w_{v,t}\,\gamma_6} + \boldsymbol{Z_{h,i,t}\gamma_7} + \boldsymbol{Z_{m,v,t}\,\gamma_8} + \boldsymbol{S_{v,t}\gamma_9} + c_i + \varepsilon_{i,t}$

(7) $SFM_{i,t} = \boldsymbol{D_g\gamma} + c_i + \varepsilon_{i,t}$

Equation 7 is a more compact representation of equation 6, and $\boldsymbol{D_g}$ and $\boldsymbol{\gamma}$ capture, respectively, all the explanatory variables and parameters in equation 6. *SFM* represents the dependent variable of interest, which is either: (i) a binary variable equal to one if a given SFM practice was used by household *i* in the main season of agricultural year *t* (and equal to zero otherwise); (ii) the household's SI category in that agricultural year; or (iii) the household's intensity of inorganic fertilizer use on maize (in kg/acre). (The particular estimators used in each case are discussed below.) Estimating models for the intensity of organic fertilizer use or intercropping is not feasible due to a lack of reliable data. We also attempted to estimate models for the proportion of the household's maize area under each SFM practice and under each SI category; however, many of these models did not converge, so this analysis was dropped.

Continuing with equation 6, the household's predicted maize price is $\widehat{P_{i,t}^{m}}$ (as a proxy for its expected maize price per section 6.1) and the lagged bean price is P_i^o (as a proxy for its other expected crop prices). We choose the bean price as a proxy for the price of legumes in general due to the popularity of beans in maize-legume intercrops in Kenya (see table 1). A_t is the household's landholding size. $L_{i,t}$ is the household's labor endowment. $O_{i,t,}$ is an indicator variable for whether the household had off-farm income in the previous survey. $\boldsymbol{w_{v,t}}$ is a vector of input prices (for inorganic fertilizer, maize seed, bean seed, agricultural labor, and land rental). $\boldsymbol{Z_{h,i,t}}$ is a vector of household characteristics including the sex, age, and education of the household head and the household's productive assets. In addition, $\boldsymbol{Z_{h,i,t}}$ captures the proportion of the household's maize land under various tenure arrangements with the base being rented-in land, and other tenure types being family owned land, land owned without a deed, and land owned with a deed. A 0.00 would represent no maize land in a particular tenure category, while a 1.00 represents that all of the maize land cultivated by a household is in a specific tenure category. $\boldsymbol{Z_{m,v,t}}$ is a vector of non-price market characteristics, such as distances to the nearest market, nearest extension service, road, and NCPB depot, among others.[10] This $\boldsymbol{Z_{m,v,t}}$ variable also contains the mean tropical livestock units (TLUs) owned by households in household i's village in the prior season; this variable is used as a proxy for the availability of animal manure in the village. $\boldsymbol{S_{v,t}}$ is as defined above. See table 5 for a full listing and summary statistics for the variables included in the SFM regressions and table 6 for summary statistics for the various dependent variables used in this part of the analysis.

[10] In addition to being engaged in maize marketing, the NCPB began subsidizing fertilizer and maize seed during the study period. Households purchase the subsidized inputs at NCPB depots. Access to the subsidy is controlled for in our regressions via the inclusion of the distance to the nearest NCPB depot variable.

Table 5: Summary statistics of explanatory variables in the SFM adoption regressions

Explanatory variables	Mean	Std. Dev.
Predicted maize output price (real 2010 Ksh/kg)	19.426	2.103
Bean output price (real 2010 Ksh/kg, village median)	34.473	17.317
Maize seed price (real 2010 Ksh/kg, village median)	68.180	36.485
Bean seed price (real 2010 Ksh/kg, village median)	10.577	8.065
DAP fertilizer price (real 2010 Ksh/kg, village median)	57.259	5.141
Farm wage (real 2010 Ksh/hour, village median)	20.677	5.555
Land rental rate (real 2010 Ksh/acre/year, village median)	4351.360	1687.427
Total landholdings owned as of previous survey (acres)	0.854	0.354
Number of prime age adults (age 15 to 59)	3.279	1.826
=1 if the HH had off farm income in the previous survey	8.565	19.562
=1 if female headed	0.202	0.402
Age of the HH head (years)	58.469	12.996
=1 if lower primary was the highest level of education	0.082	0.275
=1 if upper primary was the highest level of education	0.429	0.495
=1 if secondary was the highest level of education	0.239	0.426
=1 if post-secondary was the highest level of education	0.081	0.273
Value of productive assets as of previous survey (1000s of real 2010 Ksh)	0.300	3.178
Tropical Livestock Units owned as of one year ago	4.277	8.034
HH's proportion of maize land that is family owned	0.021	0.134
HH's proportion of maize land that is owned with a deed	0.511	0.477
HH's proportion of maize land that is owned without a deed	0.325	0.445
Km to the nearest NCPB depot	19.689	14.320
Km to the nearest fertilizer seller	3.452	3.261
Km to the nearest market place for farm produce	4.425	4.245
Km to the nearest motorable road	0.447	0.909
Km to the nearest extension service	5.096	4.844
Proportion of villagers that received credit, in cash or in kind	0.526	0.262
Village level average TLU per acre in prior survey	0.617	0.332
=1 if year is 2010	0.483	0.500
Average rain in prior six main cropping seasons (mm)	576.033	179.312
Average rain stress in prior six main cropping seasons	0.279	0.202

Source: Author's calculations. See text for details on data sources.

Notes: N=1,296. Tropical Livestock Units are defined as: cattle = 0.7, sheep & goats = 0.1, pigs = 0.2, chickens = 0.01, rabbits = 0.01. Agro-ecological zone dummies are omitted from this table but are included in the regression. In cases where values as of the previous survey are used, it is because the survey instrument captured values as of the time of interview for those questions, which would have been after SFM decisions were made. We use values as of the previous survey wave to ensure that these values are pre-determined at the time that SFM decisions were made.

Table 6. Summary statistics for the SFM dependent variables used in the analysis

Dependent variable	Mean	Std. Dev.
=1 if the HH used inorganic fertilizer on any maize plot	0.850	0.382
=1 if the HH used organic fertilizer on any maize plot	0.407	0.478
=1 if the HH intercropped maize and legumes	0.831	0.436
HH's intensity of inorganic fertilizer use on maize (kg/acre)	58.357	54.591
=1 if the HH is in the "None" category (not used in regressions)	0.015	0.133
=1 if the HH is in the "Intensification" category	0.115	0.344
=1 if the HH is in the "Sustainable" category	0.131	0.331
=1 if the HH is in the "Weak SI" category	0.536	0.499
=1 if the HH is in the "Strong SI" category	0.203	0.389

Source: Author's calculations. See text for details on data sources.
Note: N=1,296.

6.2.1. Logit models for the adoption of individual SFM practices

As a first analysis, we examine the factors affecting household-level adoption decisions for the individual SFM practices (maize-legume intercropping, use of inorganic fertilizer, and use of organic fertilizer). In this case,

$$(8)\ SFM_{i,t} = \begin{cases} 1 \text{ if household } i \text{ applies a particular practice in agricultural year } t \\ 0 \text{ otherwise} \end{cases}$$

These models are estimated via maximum likelihood CRE logistic regression. The use of CRE here and for the other second step models avoids the incidental parameters problem associated with using an FE approach in the context of nonlinear-in-parameters econometric models, especially when the panel is short as it is here. The incidental parameters problem causes FE logit estimates, for example, to be inconsistent (Wooldridge 2010, p. 271). Equation 9 shows the unobserved effects logit specification in which Λ represents the logistic function (Wooldridge 2013).

$$(9)\ P\left(SFM_{i,t} = 1 \middle| \boldsymbol{D_g}, c_i\right) = \Lambda(\alpha_0 + \boldsymbol{D_g}\boldsymbol{\gamma} + c_i)$$
$$\text{where } \Lambda(.) = \exp(.)/[1 + \exp(.)]$$

Recall that one element of $\boldsymbol{D_g}$ is the predicted price of maize $\widehat{p_{i,t}^{m}}$. This is a generated regressor (i.e., it is generated from a first-stage regression), so we correct the standard errors via bootstrapping in all second step regressions, as was done in Mason, Jayne, and Myers (2015) and Mather and Jayne (2011).

6.2.2. Multinomial logit model of maize SI category (SFM practice combinations)

A CRE multinomial logit regression is used when the dependent variable is the household-level maize SI category per table 3. In the CRE multinomial logit regression, the dependent variable represents the four analytical SI categories: "Intensification" (assigned a value of 1), "Sustainable" (assigned a value of 2), "Weak SI" (assigned a value of 3), and "Strong SI" (assigned a value of 4). (Recall that we exclude the "None" category because so few households (only 1.5%) are in it.) Note that in the multinomial logit context, the value that the dependent variable takes on in no way indicates an order (i.e., 4 is not better or worse, or more or less than 2) (McFadden 1980, Wooldridge 2010). Equation 10 is the basic form of an unobserved effects multinomial logit model, where $SIcat$ is the SI category of the household, and b takes the value associated with this category.

$$(10)\ P\left(SIcat = b \middle| \boldsymbol{D_g}, c_i\right) = \frac{\exp(\boldsymbol{D_g}\boldsymbol{\gamma} + c_i)}{1 + \sum_{h=1}^{4} \exp(\boldsymbol{D_g}\boldsymbol{\gamma} + c_i)}, b = 1, 2, 3, or\ 4$$

After estimation via maximum likelihood, average partial effects (APEs) are calculated. This allows us to identify how a marginal change in a given determinant affects the probability of a household being in a given SI category (Wooldridge 2010). APEs are reported for all four analytical SI categories (in other words there is no base category) and APEs sum to zero across the four categories (because an increase in the probability of a given SI category necessarily implies a corresponding decrease in the other three categories combined).

6.2.3. Tobit model for the intensity of inorganic fertilizer use on maize

When the dependent variable is the household-level intensity of inorganic fertilizer use on maize (measured as the household-level total kg of inorganic fertilizer applied to maize divided by the household total acres of maize), we use a CRE Tobit model. We do so because intensity of fertilizer use is a corner solution, with a non-trivial percentage of maize-growing households (15.0%) applying zero kg of fertilizer per acre of maize.

7. Results

We begin by reporting the first step results: the factors affecting the maize price a household receives at harvest. These results are used to compute the household's predicted maize price. We then report the second step results: the effects of this maize price and other factors on the household's SFM practice and SI adoption decisions.

7.1. Maize price regression results

Estimation results from the regression of households' maize price received at harvest on our theoretical determinants observable to households at the time they make SFM practice decisions are shown in table 7. There are three specifications: column A is the main specification as described in the empirical strategy section; column B is a robustness check and includes only purely exogenous variables (i.e., excludes household characteristics); and column C is the main specification plus the Tobit residuals to test and control for possible selection bias due to incidental truncation as discussed in section 6.1 (because we only observe the maize price received for households that sell maize). The results in all three columns are quite similar, which increases our confidence in the results. The Tobit residuals are not statistically significant in column C (P=0.86), indicating that we fail to reject the null hypothesis of no selection bias. Given these results, we use the main specification (column A) in the second step analyses of the effects of the expected maize price on households' SFM/SI decisions.

One finding of interest in table 7 is that a one shilling increase in the lagged NCPB maize price raises a household's expected maize price by an average of 0.13 Ksh/kg, *ceteris paribus*; that is, roughly 13% of a marginal increase in the NCPB maize price is passed on to the household's expected maize price. The positive effect of the lagged NCPB price on households' expected maize price is consistent with *a priori* expectations and with previous findings in the literature (e.g., Jayne, Myers, and Nyoro (2008) and Mather and Jayne (2011)).

The extent to which the other statistically significant determinants of a household's expected maize price conform to *a priori* expectations is more variable (see table 7). Households in areas with higher average rainfall in the last six main cropping seasons generally receive a lower maize price at the next harvest, which may be due to higher maize supplies in such areas. But areas with more rain stress periods per year in the last six main cropping seasons also get lower maize prices, on average, at the next harvest; more research is needed to understand this result. Households with more land receive a lower maize price, on average; while we initially expected this effect to be positive (e.g., households that produce more get a higher price for the maize they sell because they are selling in larger quantities), the negative effect of landholding on the maize price received may be explained by maize production levels in general being higher in areas where households have larger landholdings, which would be expected to put downward pressure on maize prices. Finally, while one might expect households with a bicycle to be able to fetch a higher price for their maize, the results suggest the opposite. If our other distance variables do not adequately capture market access, this negative effect of bike ownership might simply reflect that such households are in more remote areas and need a bike to reach markets.

Table 7. Maize price regression results (CRE-POLS)

	(A)			(B)			(C)		
Dependent variable: Maize price received at harvest (real Ksh/Kg)	Coef	Sig	p-val	Coef	Sig	p-val	Coef	Sig	p-val
Maize seed price (real 2010 Ksh/kg, village median)	-0.017	*	0.096	-0.016		0.124	-0.017	*	0.075
DAP fertilizer price (real 2010 Ksh/kg, village median)	0.013		0.820	0.011		0.855	0.013		0.809
Farm wage (real 2010 Ksh/hour, village median)	0.022		0.814	0.016		0.855	0.022		0.806
Land rental rate (real 2010 Ksh/acre/year, village median)	-0.0004		0.338	-0.0004		0.397	-0.0004		0.314
Plentiful season average wholesale price of maize (real 2010 Ksh/kg)	0.016		0.879	0.018		0.855	0.016		0.877
Farmgate NCPB maize price (t-1, real 2010 Ksh/kg)	0.127	**	0.036	0.120	**	0.045	0.127	**	0.032
NCPB purchases of maize at division level (MT, t-1)	-0.002		0.461	-0.003		0.291	-0.002		0.469
=1 if female headed	-2.352		0.211	-		-	-2.352		0.233
Age of the HH head (years)	-0.029		0.648	-		-	-0.029		0.716
=1 if lower primary was the highest level of education	-0.822		0.218	-		-	-0.822		0.234
=1 if upper primary was the highest level of education	0.012		0.989	-		-	0.012		0.989
=1 if secondary was the highest level of education	-0.566		0.685	-		-	-0.566		0.688
=1 if post-secondary was the highest level of education	0.463		0.800	-		-	0.463		0.806
Number of prime age adults (age 15 to 59)	0.105		0.564	-		-	0.105		0.551
Total landholdings owned as of previous survey (acres)	-0.069	**	0.043	-		-	-0.069	**	0.046
Value of productive assets as of previous survey (1000s of real 2010 Ksh)	-0.001		0.375	-		-	-0.001		0.662
Tropical Livestock Units owned as of one year ago	0.008		0.789	-		-	0.008		0.837
=1 if the household had a car, truck, or motorcycle in the prior survey	-1.167		0.499	-		-	-1.167		0.503
=1 if the HH had a cart in the prior survey	-0.291		0.808	-		-	-0.291		0.808
=1 if the HH had a bike in the prior survey	-1.161	*	0.066	-		-	-1.161	*	0.053
=1 if the HH had stores in the prior survey	0.136		0.811	-		-	0.136		0.802
Km to the nearest market place for farm produce	0.002		0.973	-0.002		0.970	0.002		0.975
Km to the nearest motorable road	-0.114		0.529	-0.104		0.558	-0.114		0.559
Km to the nearest fertilizer seller	0.069		0.399	0.065		0.385	0.069		0.426
Km to the nearest place to get extension advice	0.001		0.988	0.012		0.818	0.001		0.990
=1 if year is 2010	1.767	**	0.043	1.802	**	0.035	1.767	**	0.045
Average rain in prior six main cropping seasons (mm)	-0.017	**	0.030	-0.018	**	0.015	-0.017	**	0.030
Average rain stress in prior six main cropping seasons	-12.903	*	0.096	-12.582		0.115	-12.903	*	0.091
Residuals for selection bias test	-		-	-		-	-0.00001		0.864

Source: Author's calculations. See text for details on data sources.

Notes: N=615. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. P-values based on standard errors clustered at the household level. Standard errors for column (C) bootstrapped (500 complete replications) to account for the generated regressor (Tobit residuals). Agro-ecological zones are included in the regressions, however not included in this table.

7.2. Determinants of inorganic fertilizer use on maize at the household level

The results from the CRE logit regression for the determinants of inorganic fertilizer on maize use are reported in column A of table 8. The results suggest that a household's expected (predicted) maize price has no statistically significant effect on the household's decision to use inorganic fertilizer or not. The lagged bean price similarly has no effect on this decision, nor do most of the input prices. However, the results do suggest that an increase in the land rental price is associated with a reduction in the probability that a household uses inorganic fertilizer. Overall, expected output prices and input prices seem to have little bearing on a household's decision to use inorganic fertilizer.

Some other variables do have statistically significant effects on this decision, however. For example, household that had off-farm income as of the previous survey were less likely, on average, to use inorganic fertilizer. This is not what we had expected but may be due to households with off-farm income relying less on and investing less in their maize production activities. Female-headed households are less likely to use inorganic fertilizer, which is consistent with previous findings in the literature (e.g., Kassie et al. 2015; Marenya and Barrett 2007; Marenya and Barrett 2009; Murendo et al. 2016). Moreover, households with stronger forms of land tenure on a higher proportion of household maize land have a lower likelihood of inorganic fertilizer application, on average. This is consistent with the findings of some previous studies (e.g., Asfaw, Manuela, and Lipper 2015; Kassie et al. 2013; Kassie and Holden 2007). Finally, more frequent periods of rainfall stress in past main cropping seasons is associated with a reduced probability of inorganic fertilizer use. This makes sense given that inorganic fertilizer use is most beneficial when there is adequate rainfall or irrigation.

7.3. Determinants of maize-legume intercropping at the household level

The results from the CRE logit regression for the determinants of a household's decision to use maize-legume intercropping are reported in column B of table 8. Similar to the inorganic fertilizer results, we find little evidence that changes in expected output prices or in input prices affect households' decisions to practice maize-legume intercropping. In fact, only one explanatory variable is statistically significant in this regression: a higher proportion of villagers receiving credit is associated with a decrease in a household's probability of using maize-legume intercropping.

7.4. Determinants of organic fertilizer use on maize at the household level

The results from the CRE logit regression for the determinants of organic fertilizer use on maize are reported in column C of table 8. As was the case for inorganic fertilizer use and maize-legume intercropping, changes in a household's expected maize and bean prices have no statistically significant effect on a household's decision to use organic fertilizer. However, some input prices do affect this decision. The most intuitive finding is that an increase in the DAP fertilizer price is associated with an increase in the probability that a household uses organic fertilizer, suggesting that these two inputs are complements. The result for the effect of the farm wage is less intuitive, however, as we find that an increase in the farm wage is associated with an increased probability of organic fertilizer use, on average and other factors constant. This is contrary to *a priori* expectations given that organic fertilizer use is a labor-intensive endeavor. In addition, as rental rates also increase we find a lower likelihood of organic fertilizer use. The final statistically significant input price effect is that an increase in the maize seed price is associated with an increased probability of organic fertilizer use.

Some other notable findings from this regression include that an increase in the proportion of a household's maize land that is under more secure forms of tenure is associated with an increase in the probability of organic fertilizer use. This is consistent with previous findings in the literature that greater land tenure security is associated with greater investment in soil health (e.g., Kassie et al. 2013; Kassie et al. 2015; Manda et al. 2016; Ndiritu, Kassie, and Shiferaw 2014). Also consistent with *a priori* expectations is the finding that a greater concentration of livestock in the household's village is associated with a greater likelihood of organic fertilizer use. Finally, our results suggest that female headed households are more likely to use organic fertilizer.

For all three SFM practices, when we assume naïve expectations instead of using the predicted maize price as a proxy for the household's expected maize price, we continue to find that the expected maize price has no statistically significant effect on the probability of use of a given practice. This is also the case for maize-legume intercropping and organic fertilizer when we assume perfect foresight with respect to the maize price. However, for inorganic fertilizer, when perfect foresight is assumed, we find that an increase in the maize output price is associated with an increase in the probability that a household uses inorganic fertilizer. Nonetheless, the weight of the evidence (eight of nine models) suggests that an increase in a household's expected maize price has no effect on its likelihood of using the SFM practices studied here.[11] This may be due to household's production and consumption decisions being non-separable. When there are multiple market failures, households' responses to prices are often the

[11] The nine models are the logits for each of the three SFM practices and with three different assumptions each about how households form maize price expectations: (i) a quasi-rational expectations-like approach (as reported in the main results and described in the empirical strategy section), (ii) naïve expectations, and (iii) perfect foresight. The results for the latter two are available from the author upon request.

opposite of what we would expect in the separable case or households are not sensitive to changes in market prices (de Janvry et al. 1991).

Table 8. Factors affecting the probability of use of a given SFM practice on one or more maize plots (CRE logit results)

Dependent variable	(A) Inorganic fertilizer (=1)			(B) Maize-legume intercropping (=1)			(C) Organic fertilizer (=1)		
Explanatory variables	APE	Sig	p-val	APE	Sig	p-val	APE	Sig	p-val
Predicted maize output price (real 2010 Ksh/kg)	0.005		0.739	0.011		0.450	0.008		0.648
Bean output price (real 2010 Ksh/kg)	0.000004		0.996	-0.001		0.173	-0.0001		0.943
Maize seed price (real 2010 Ksh/kg, village median)	-0.0005		0.365	0.0004		0.412	0.001	*	0.087
Bean seed price (real 2010 Ksh/kg, village median)	-0.003		0.139	0.001		0.536	0.003		0.263
DAP fertilizer price (real 2010 Ksh/kg, village median)	-0.004		0.131	0.004		0.133	0.007	***	0.006
Farm wage (real 2010 Ksh/hour, village median)	0.00002		0.220	0.00001		0.515	0.007	*	0.074
Land rental rate (real 2010 Ksh/acre/year, village median)	-0.010	**	0.017	-0.004		0.297	-0.00004	**	0.025
Total landholdings owned as of previous survey (acres)	-0.0002		0.960	-0.001		0.680	0.008	*	0.072
Number of prime age adults (age 15 to 59)	-0.009		0.309	0.011		0.352	0.007		0.473
=1 if the HH had off farm income in the previous survey	-0.082	***	0.008	0.046		0.267	0.095	***	0.005
=1 if female headed	-0.283	***	0.005	-0.007		0.943	0.203	*	0.052
Age of the HH head (years)	-0.005		0.353	0.005		0.294	0.000		0.994
=1 if lower primary was the highest level of education	-0.027		0.592	0.023		0.619	0.022		0.678
=1 if upper primary was the highest level of education	0.063		0.243	0.026		0.609	-0.066		0.223
=1 if secondary was the highest level of education	0.120		0.129	0.044		0.560	-0.059		0.458
=1 if post-secondary was the highest level of education	0.066		0.514	0.055		0.557	-0.052		0.589
Value of productive assets as of previous survey (1000s of real 2010 Ksh)	0.011		0.849	0.012		0.856	-0.023		0.491
Tropical Livestock Units owned as of one year ago	0.001		0.519	-0.00002		0.994	-0.0001		0.981
HH's proportion of maize land that is family owned	-0.092		0.389	0.006		0.964	0.012		0.906
HH's proportion of maize land that is owned with a deed	-0.167	***	0.004	-0.009		0.886	0.125	**	0.034
HH's proportion of maize land that is owned without a deed	-0.127	**	0.033	-0.033		0.613	0.113	*	0.072
Km to the nearest NCPB depot	-0.002		0.266	-0.001		0.397	0.002		0.134
Km to the nearest fertilizer seller	-0.005		0.424	0.004		0.468	0.009		0.182
Km to the nearest market place for farm produce	-0.003		0.365	0.002		0.595	0.006		0.129
Km to the nearest motorable road	-0.013		0.488	0.013		0.453	-0.002		0.916
Km to the nearest extension service	-0.0004		0.908	-0.003		0.243	-0.005		0.190
Proportion of villagers that received credit, in cash or in kind	-0.102		0.203	-0.312	***	0.000	0.194	**	0.021
Village level average TLU per acre in prior survey	-0.007		0.911	0.065		0.323	0.127	**	0.048
=1 if year is 2010	-0.093	*	0.074	0.020		0.661	0.062		0.263
Average rain in prior six main cropping seasons (mm)	0.0004		0.464	0.001		0.231	0.0005		0.477
Average rain stress in prior six main cropping seasons	-0.895	**	0.038	0.282		0.572	1.695	***	0.001

Source: Author's calculations. See text for details on data sources.

Notes: N=1,296. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. p-values based on standard errors clustered at the household level and bootstrapped (500 complete replications) to account for the generated regressor (expected maize price predicted from first stage regression).

7.5. Determinants of the intensity of inorganic fertilizer use on maize

Table 9 reflects the results from a CRE Tobit regression of factors affecting the household's intensity of chemical fertilizer use on maize. Again, a change in the expected maize price has no effect on the household's intensity of inorganic fertilizer use. However, an increase in the price of beans is correlated with a decrease in the intensity of chemical fertilizer use. This may be because households invest more in bean production and less in maize production when they expected a higher bean output price. As anticipated, an increase in the DAP fertilizer price is associated with a reduction in the intensity of inorganic fertilizer use on maize. None of the other input prices have a statistically significant effect on this decision.

Other notable findings in table 9 include a positive relationship between landholding size and a household's chemical fertilizer application rate. Greater access to credit in the household's village and higher average rainfall in the past six main cropping seasons are also associated with an increase in the intensity of inorganic fertilizer use, as expected. Somewhat surprisingly, however, an increase in the distance to the nearest NCPB depot is associated with an increase in inorganic fertilizer use. While further research is needed to better understand what is driving this result, it may be that NCPB activities (be it buying maize or selling subsidized fertilizer) crowd out private sector activity, the net result being greater fertilizer demand in areas farther away from NCPB depots.

Table 9. Factor affecting the household's intensity of inorganic fertilizer use on maize (CRE Tobit results)

Dependent variable / Explanatory variables	Intensity of inorganic fertilizer use (kg/acre) APE	Sig	p-val
Predicted maize output price (real 2010 Ksh/kg)	-1.022		0.572
Bean output price (real 2010 Ksh/kg, village median)	-0.186	**	0.037
Maize seed price (real 2010 Ksh/kg, village median)	-0.072		0.205
Bean seed price (real 2010 Ksh/kg, village median)	-0.237		0.247
DAP fertilizer price (real 2010 Ksh/kg, village median)	-1.009	***	0.000
Farm wage (real 2010 Ksh/hour, village median)	-0.527		0.132
Land rental rate (real 2010 Ksh/acre/year, village median)	0.002		0.326
Total landholdings owned as of previous survey (acres)	0.901	***	0.009
Number of prime age adults (age 15 to 59)	-0.275		0.766
=1 if the HH had off farm income in the previous survey	-2.893		0.419
=1 if female headed	-13.708		0.210
Age of the HH head (years)	-1.191	**	0.015
=1 if lower primary was the highest level of education	-2.448		0.663
=1 if upper primary was the highest level of education	-10.597	*	0.075
=1 if secondary was the highest level of education	-6.273		0.485
=1 if post-secondary was the highest level of education	-8.163		0.506
Value of productive assets as of previous survey (1000s of real 2010 Ksh)	-0.973		0.534
Tropical Livestock Units owned as of one year ago	0.375		0.194
HH's proportion of maize land that is family owned	-1.801		0.882
HH's proportion of maize land that is owned with a deed	-5.841		0.258
HH's proportion of maize land that is owned without a deed	-2.866		0.599
Km to the nearest NCPB depot	0.230	*	0.092
Km to the nearest fertilizer seller	0.508		0.375
Km to the nearest market place for farm produce	-0.157		0.689
Km to the nearest motorable road	1.708		0.191
Km to the nearest extension service	0.137		0.616
Proportion of villagers that received credit, in cash or in kind	24.211	***	0.002
Village level average TLU per acre in prior survey	18.306	***	0.003
=1 if year is 2010	4.050		0.467
Average rain in prior six main cropping seasons (mm)	0.109	*	0.063
Average rain stress in prior six main cropping seasons	-2.462		0.958

Source: Author's calculations. See text for details on data sources.
Notes: N=1,296. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. p-values based on standard errors clustered at the household level and bootstrapped (500 complete replications) to account for the generated regressor (expected maize price predicted from first stage regression).

7.6. Determinants of the household's SI category

Our final set of results is from the CRE multinomial logit model for the household's SI category (table 10). Before we begin the table needs some explanation. The dependent variables appear to have four different values per variable. This is due to the four different SI categories. Each outcome (SI category) is evaluated in comparison to the other outcomes. This is why they all sum to 0.00, one category gains probability for a change in the dependent variable and the other categories (combined) lose probability.

As was the case for the previous regressions, the results in table 10 suggest that the expected maize price is not a statistically significant determinant of a household's SFM decisions (in this case, their SI category). Similarly, the bean output price does not affect a household's SI category, nor do most input prices. The probability of a household choosing one SI category is significantly increased given an increase in the bean seed price ("Sustainable") and by the farm wage rate ("Strong SI") but the results are weak at best. Overall, we find very little evidence to suggest that expected output prices or input prices play an important role in households' SI category decisions.

Little else is statistically significant in this regression. The strongest findings are as follows. First, an increase in the share of a household's maize land that is owned with a title deed raises the probability that a household is in the Strong SI category by 13.1 percentage points and reduces the probability of it being in the Weak SI category by 17.2 percentage points. This implies that an increase in land tenure security is associated with a shift toward the highest form of SI considered in this study. Second, greater access to credit in the household's village is associated with shifts toward Intensification (by 19.7 percentage points) and Strong SI (by 17.2 percentage points) and away from Weak SI (by 36.0 percentage points).

Table 10. Factors affecting the SI category of the household (CRE multinomial logit results)

Dependent variable (SI category) Explanatory variables		APE	Sig	p-val
Predicted maize output price (real 2010 Ksh/kg)				
	Intensification	-0.015		0.207
	Sustainable	0.010		0.544
	Weak SI	0.024		0.222
	Strong SI	-0.019		0.250
Bean output price (real 2010 Ksh/kg, village median)				
	Intensification	0.0004		0.612
	Sustainable	0.002		0.142
	Weak SI	0.000		0.682
	Strong SI	-0.001		0.101
Maize seed price (real 2010 Ksh/kg, village median)				
	Intensification	0.00002		0.973
	Sustainable	-0.001		0.109
	Weak SI	0.001		0.449
	Strong SI	0.0003		0.622
Bean seed price (real 2010 Ksh/kg, village median)				
	Intensification	-0.003		0.227
	Sustainable	0.004	**	0.049
	Weak SI	-0.003		0.270
	Strong SI	0.001		0.591
DAP fertilizer price (real 2010 Ksh/kg, village median)				
	Intensification	-0.002		0.496
	Sustainable	0.002		0.407
	Weak SI	0.003		0.432
	Strong SI	-0.004		0.250
Farm wage (real 2010 Ksh/hour, village median)				
	Intensification	0.004		0.328
	Sustainable	-0.002		0.555
	Weak SI	-0.009		0.106
	Strong SI	0.007	*	0.093
Land rental rate (real 2010 Ksh/acre/year, village median)				
	Intensification	-0.00002		0.360
	Sustainable	0.00001		0.705
	Weak SI	0.00003		0.264
	Strong SI	-0.00002		0.385
Total landholdings owned as of previous survey (acres)				
	Intensification	-0.001		0.687
	Sustainable	-0.006		0.116
	Weak SI	0.002		0.744
	Strong SI	0.005		0.424
Number of prime age adults (age 15 to 59)				
	Intensification	-0.020	**	0.028
	Sustainable	0.005		0.592
	Weak SI	0.013		0.268
	Strong SI	0.001		0.933

Table 10 (Cont'd)

Dependent variable (SI category) Explanatory variables	APE	Sig	p-val
=1 if the HH had off farm income in the previous survey			
Intensification	-0.057	*	0.097
Sustainable	0.011		0.700
Weak SI	0.019		0.661
Strong SI	0.027		0.443
=1 if female headed			
Intensification	-0.110		0.224
Sustainable	0.135		0.365
Weak SI	-0.199		0.115
Strong SI	0.174		0.279
Age of the HH head (years)			
Intensification	-0.011	*	0.053
Sustainable	0.004		0.589
Weak SI	0.006		0.463
Strong SI	-0.0001		0.993
=1 if lower primary was the highest level of education			
Intensification	-0.042		0.344
Sustainable	-0.002		0.972
Weak SI	0.00004		0.999
Strong SI	0.043		0.397
=1 if upper primary was the highest level of education			
Intensification	-0.021		0.635
Sustainable	-0.014		0.806
Weak SI	0.090		0.149
Strong SI	-0.055		0.371
=1 if secondary was the highest level of education			
Intensification	-0.016		0.816
Sustainable	-0.072		0.321
Weak SI	0.106		0.238
Strong SI	-0.019		0.838
=1 if post-secondary was the highest level of education			
Intensification	-0.056		0.434
Sustainable	0.041		0.728
Weak SI	0.055		0.630
Strong SI	-0.041		0.726
Value of productive assets as of prior survey (1000s of real 2010 Ksh)			
Intensification	-0.009		0.824
Sustainable	-0.002		0.989
Weak SI	0.023		0.896
Strong SI	-0.011		0.959
Tropical Livestock Units owned as of one year ago			
Intensification	-0.001		0.766
Sustainable	-0.002		0.536
Weak SI	-0.0001		0.989
Strong SI	0.002		0.602

Table 10 (Cont'd)

Dependent variable (SI category) Explanatory variables	APE	Sig	p-val
HH's proportion of maize land that is family owned			
Intensification	0.056		0.985
Sustainable	0.044		0.994
Weak SI	-0.180		0.990
Strong SI	0.080		0.997
HH's proportion of maize land that is owned with a deed			
Intensification	0.009		0.860
Sustainable	0.032		0.617
Weak SI	-0.172	**	0.027
Strong SI	0.131	**	0.047
HH's proportion of maize land that is owned without a deed			
Intensification	-0.0001		0.998
Sustainable	0.046		0.493
Weak SI	-0.121		0.139
Strong SI	0.075		0.291
Km to the nearest NCPB depot			
Intensification	0.0004		0.735
Sustainable	0.001		0.303
Weak SI	-0.002		0.202
Strong SI	0.001		0.675
Km to the nearest fertilizer seller			
Intensification	-0.001		0.799
Sustainable	-0.004		0.557
Weak SI	0.006		0.364
Strong SI	-0.001		0.857
Km to the nearest market place for farm produce			
Intensification	-0.001		0.841
Sustainable	-0.002		0.645
Weak SI	-0.005		0.358
Strong SI	0.007		0.159
Km to the nearest motorable road			
Intensification	-0.007		0.643
Sustainable	0.017		0.245
Weak SI	-0.013		0.599
Strong SI	0.003		0.870
Km to the nearest extension service			
Intensification	-0.0002		0.923
Sustainable	0.003		0.406
Weak SI	0.001		0.796
Strong SI	-0.003		0.465
Proportion of villagers that received credit, in cash or in kind			
Intensification	0.197	**	0.011
Sustainable	-0.010		0.897
Weak SI	-0.360	***	0.000
Strong SI	0.172	**	0.036

Table 10 (Cont'd)

Explanatory variables	Dependent variable (SI category)	APE	Sig	p-val
Village level average TLU per acre in prior survey				
	Intensification	-0.036		0.558
	Sustainable	-0.038		0.488
	Weak SI	0.007		0.929
	Strong SI	0.067		0.329
=1 if year is 2010				
	Intensification	0.014		0.759
	Sustainable	-0.062		0.208
	Weak SI	-0.044		0.512
	Strong SI	0.092	*	0.082
Average rain in prior six main cropping seasons (mm)				
	Intensification	-0.0002		0.651
	Sustainable	-0.001		0.197
	Weak SI	0.00005		0.949
	Strong SI	0.001		0.199
Average rain stress in prior six main cropping seasons				
	Intensification	-0.406		0.401
	Sustainable	-0.124		0.780
	Weak SI	-0.214		0.723
	Strong SI	0.745		0.143

Source: Author's calculations. See text for details on data sources.
Notes: N=1,266. This is due to removing 30 observations for households that fell into the "None" category in one or both survey waves (2007 and 2010). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. p-values based on standard errors clustered at the household level and bootstrapped (500 complete replications) to account for the generated regressor (expected maize price predicted from first step regression).

8. Conclusions and policy implications

Soil degradation is a serious concern in Kenya as it is in many other countries in SSA. Adoption of SFM practices and SI can slow soil degradation and, over time, improve soil fertility. Given the prime importance of maize as a staple food consumed by and a crop produced by smallholder farmers in Kenya, SI of maize production is particularly critical. In this study, we focused on three SFM practices that can contribute to SI of maize production and that are commonly but not universally used in Kenya: inorganic fertilizer, organic fertilizer, and maize-legume intercropping. We also categorized households by their degree of SI of maize production based on which combination (if any) of these practices they used on their maize plots. Motivated by suggestions in the literature but a dearth of empirical evidence that smallholder farm households might adopt more sustainable forms of maize intensification if they expect to receive a higher maize price come harvest time, we sought to understand the role that changes in a household's expected maize price play in their SFM adoption and SI decisions. We also sought to measure how such households respond to changes in input prices, as economic theory suggests that both expected maize prices and input prices are likely to be important drivers of farmers' maize production-related technology adoption decisions.

Our three main findings are as follows. First, the expected maize price does not appear to be an important determinant of Kenyan smallholder maize-growing households' SI category or SFM practice adoption decisions. We find essentially no empirical evidence to support claims made in the literature that households are likely to respond to an increase in their expected maize price by adopting more SFM practices and by sustainably intensifying their maize production. This finding is robust to different assumptions about how households form their maize price expectations.

Second, input prices show very few statistically significant effects on SFM adoption and SI category decisions, and in some instances when they are statistically significant, the price effects are opposite of what we would expect based on pure producer theory. However, we assume non-separability and multiple market failures and, in such cases, as discussed in de Janvry et al. (1991), households often have unexpected responses or no response to changes in market prices. Exceptions where input prices concur with our *a priori* expectations are that an increase in the DAP fertilizer price is associated with an increased probability of use of organic fertilizer on maize (suggesting inorganic and organic fertilizer are complements) and is also associated with a reduction in the intensity of fertilizer use on maize.

Third, our results, like previous studies in the literature, suggest that land tenure security is an important factor influencing some SFM practice and SI category decisions. For example, with stronger tenure security, households are more likely to adopt organic fertilizer and tend to shift away from weak SI and toward strong SI (the combined use of maize-legume intercropping, organic fertilizer, and inorganic fertilizer).

These findings point to four main policy implications. First, given our finding that Kenyan smallholder farmers' expected maize prices play little if any role in their decisions related to SFM practices and SI, efforts by the Kenyan government to raise maize producer prices in the country via the activities of its maize marketing board, the National Cereals and Produce Board, and other maize price policies are unlikely to effectively promote (nor are they likely to discourage) sustainable intensification of maize production. Second, our findings suggest that Kenyan farmers are less likely to use organic fertilizer on their maize when the inorganic fertilizer price declines. This suggests that the country's inorganic fertilizer subsidy programs may have unintended negative effects on farmers' use of organic fertilizer. Given that joint use of inorganic and organic fertilizers can increase maize yield response to inorganic fertilizer and that use of organic fertilizer can increase SOM levels, which are low in many parts of Kenya, complementary policies are needed to encourage organic fertilizer use. Third, given Kenyan smallholder farmers' lack of sensitivity to input prices other than the inorganic fertilizer price in making their SFM adoption and SI category decisions, input price policies (other than those for inorganic fertilizer) are unlikely to be effective at changing farmer behavior related to SFM practices and SI. Finally, given our finding that stronger land tenure rights are associated with households shifting from the weak SI to the strong SI category, policies and programs to improve land tenure security (e.g., through promoting or facilitating land titling) may be a promising way to foster sustainable intensification of maize production in Kenya.

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