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Tradeoffs and Complementarities in the Adoption of Improved Seeds, Fertilizer, and Natural Resource Management Technologies in Kenya

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Abstract

There is widespread consensus that agricultural technology has an important role to play for poverty reduction and sustainable development. There is less consensus, however, about the types of technologies that are best suited for smallholder farmers in Africa. While some consider natural resource management (NRM) technologies as most appropriate, others propagate input intensification with a stronger role of the private sector. In the public debate, the two strategies are often perceived as incompatible. Most existing adoption studies focus on individual technologies, so that comparisons across technologies in the same context are not easily possible. We use representative data from maize-producing households in Kenya and a multivariate probit model to analyze the adoption of different types of technologies simultaneously. Results indicate that NRM technologies and strategies that build on external inputs are not incompatible. Interesting complementarities exist, which are not yet sufficiently exploited, because many organizations promote either one type of technology or the other, but rarely a combination of both.

JEL classifications: O13, O33, Q12, Q16

Keywords: Technology adoption, maize, small farms, sustainable agriculture, Africa

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1. Introduction

Growth in the agricultural sector is key to alleviating poverty and food insecurity in developing countries (World Bank, 2007). In this connection, technological innovation plays an important role. Agricultural technologies can help to increase output and thus improve access to food, as experience with the green revolution has demonstrated (Evenson and Gollin, 2003). In addition, agricultural technologies can contribute to poverty reduction, by raising the incomes of farm households and, in some cases, providing new employment opportunities for landless laborers (Winters et al., 1998; De Janvry and Sadoulet, 2001; Minten and Barrett, 2008; Noltze et al., 2013). However, especially in the African small farm sector, adoption rates of agricultural technologies remain quite low. There is also a lively debate about which type of technology is most appropriate to foster sustainable development in the small farm sector. While some consider low-external input strategies as most suitable (IAASTD, 2009), others suggest models of input intensification with a stronger role of the private sector (Pingali, 2007).

Low-external input strategies involve different agronomic practices, such as conservation tillage, other soil and water management techniques, and use of organic manure. Such improved agronomic practices are often referred to as natural resource management (NRM) technologies. Input intensification strategies, on the other hand, place higher emphasis on the use of improved seeds, mineral fertilizer, irrigation, and other productivity-enhancing inputs. Unfortunately, in the public debate the two strategies are often seen as two incompatible paradigms. Entrenched views by advocates of both paradigms are sometimes also reflected in the design of development projects that promote one or the other type of technologies, but rarely a combination of both. In reality, the two strategies are not incompatible. For instance, combining conservation agriculture with improved seeds and other external inputs can lead to positive synergistic effects (Kassie et al., 2015). Rather than searching for a general blueprint, appropriate strategies will differ from one situation to another, depending on local agroecological, socioeconomic, and market conditions.

More research is needed to better understand which technologies, and combinations of technologies, are adopted in certain situations and how sustainable innovation could be promoted. Most existing studies focus on the adoption of one specific type of technology, such as improved seeds (Nkonya et al., 1997; Becerril and Abdulai, 2010; Smale and Olwande, 2014), mineral fertilizer (Lambrecht et al., 2014), conservation agriculture (Kassie et al., 2010; Wollni et al., 2010), or other soil conservation techniques (Gebremedhin and Swinton, 2003). The data and methodologies used are often different, so that results are not easily comparable. While focusing on individual technologies is useful for many questions, studies that look across different types of technologies are also important to gain a broader picture, be able to compare, and identify complementarities and tradeoffs. Here, we intend to contribute in this direction by analyzing the adoption of multiple technologies among smallholder farmers in Kenya.

The analysis builds on a large, nationally representative data set of maize-growing farms in Kenya. Maize is grown in almost all of the country's agroecological zones, primarily by smallholders (Smale and Olwande, 2014). We specify and estimate a multivariate probit model that accounts for the fact that farmers make multiple adoption decisions simultaneously (Dorfman, 1996). In addition to farm, household, and institutional variables, we include plot-level variables, such as soil fertility and slope, as covariates in the adoption model. Noltze et al. (2012) showed that plot-level factors may significantly influence the adoption of NRM technologies in particular. Finally, we analyze how the adoption of different technologies correlates and how such correlation, or lack thereof, can be explained.

2. Types of technologies and factors influencing adoption

2.1. Input-intensive and NRM technologies

There are two broad types of technologies that are promoted for use by farmers in Kenya and other developing countries. The first type are technologies that build on external inputs such as improved seeds, chemical fertilizer, pesticides, and irrigation. In the Kenyan small farm sector, irrigation and pesticides are rarely used for maize production, so we concentrate on improved maize seeds and mineral fertilizer. Improved maize seeds include maize hybrids and open-pollinating varieties (OPVs) developed by private and public sector breeding programs. The second type of technologies are NRM practices, such as conservation agriculture, soil and water management techniques, and use of organic manure. The concrete NRM technologies included in this study are described in the following.

NRM strategies are mainly developed to deal with environmental stresses, such land degradation and nutrient depletion. Soil and water management practices such as constructing terraces or soil bunds are promoted to curb problems of soil erosion. Terraces are constructed walls that retain embankments of soil. The construction involves preparing a base for the wall, transporting construction rocks, and carefully layering the stones. Soil bunds, on the other hand, are embankments made by ridging soil on the lower side of a ditch along a slope contour (Gebremedhin and Swinton, 2003). Soil bunds can be constructed by hand digging or plowing, which is cheaper than building stone terraces but usually also less effective in terms of reducing water erosion. We consider both technologies in the adoption analysis.

Conservation agriculture aims at decreasing disturbance of the soil structure to reduce erosion and improve water and nutrient management. Conservation agriculture involves three components, namely reduced tillage (zero/minimum tillage), permanent soil cover through crop residue management (mulching), and crop rotation (Hobbs et al., 2008). In practice, these three components are not always adopted in combination, so that we consider zero tillage and crop residue management as two separate technologies in the adoption analysis. Independent of tillage practices, mulching helps to reduce soil evaporation and maximum temperatures in the soil surface layers, and to increase water infiltration, soil porosity, and aggregate stability. Finally, we consider the use of animal manure as an additional technology to improve nutrient supply and organic matter in the soil.

2.2. Factors influencing adoption

The broad literature on agricultural technology adoption suggests that there are many socioeconomic, institutional, and agroecological factors that influence individual adoption decisions by farmers. However, as is also known, the importance of each factor and the direction of influence also depend on the nature of the technology. In the following paragraphs, we discuss important groups of factors that were shown to play a role in the existing literature about the adoption of input-intensive and NRM technologies (Gollin et al, 2005; Lee, 2005). This discussion will help in selecting explanatory variables in the empirical sections below and interpreting the estimation results.

We start the discussion with socioeconomic characteristics of the farm, the farmer, and the farming household. Land area of the farm and other assets owned are often found to affect technology adoption in a positive way. This is especially true when adoption requires large investments, but has also been observed for scale-neutral technologies because asset-rich farmers are often less risk averse (Feder et al., 1985). Risk aversion can lead to slow and low adoption of agricultural technologies, especially when inputs that need to be purchased are involved. Hence, one could expect that farm size and risk aversion matter more for input-intensive technologies than for NRM technologies. Human capital is another factor that can influence adoption. Better-educated and more experienced farmers tend to adopt new technologies faster, especially when the technologies are knowledge-intensive and require changes in traditional cultivation practices (Kabunga et al., 2012). Moreover, the gender of the farmer may play an important role. Women farmers are often more constrained in their access to information and markets, so that they adopt new technologies slower than their male counterparts (FAO, 2011). Against this background one can expect that the gender of the farmer plays a more important role for input-intensive technologies. Finally, household availability of other resources required for adoption is important. NRM technologies are often more labor-intensive, so that their adoption depends on family labor availability (Lee, 2005; Wollni et al., 2010; Noltze et al., 2012). Livestock keeping facilitates the use organic manure in crop production, but complicates mulching because crop residues may be required as fodder.

Beyond farm, farmer, and household characteristics, contextual factors can be important. Infrastructure and institutional variables, such as distance to markets and access to credit and agricultural extension, were shown to influence technology adoption in many empirical studies (Feder et al., 1985). Access to extension is particularly important for NRM technologies, as they often require experimentation and adaptation to the local context (Lee, 2005: Noltze et al., 2012). Furthermore, depending on the type of technology, agroecological factors such as climate and soil conditions can matter a lot. For instance, high rainfall can stimulate weed growth and increase water logging (Kassie et al., 2010), which may negatively influence the adoption of zero tillage. With frequent droughts and other extreme weather events, farmers tend to adopt practices that involve smaller cash outlays to reduce financial risks (Hintze et al., 2003).

Most technology adoption studies consider agroecological factors at the farm or regional level. However, relevant conditions may also vary within farms, which may explain why farmers adopt certain technologies on some plots but not on others. Important plot level characteristics include plot size, slope, and soil conditions (Amsalu and De Graaff, 2006; Marenya and Barrett, 2007; Noltze et al., 2012). We expect plot characteristics to play a more important role for the adoption of NRM technologies, as these technologies are often more location-specific. For instance, soil and water management practices (terracing and soil bunds) are more relevant for locations with slopes. Plot ownership status may also play an important role, especially for investments with longer-term impacts, such as terracing.

3. Data and descriptive statistics

3.1. Data

We use data that we collected recently through a nationally representative survey of maize-growing farms in Kenya. The data include 4035 plots from 1344 farm households distributed across all six maize agroecological zones (AEZs), as defined by Hassan (1998). Households to be surveyed were selected using a stratified, two-stage random sampling procedure. In all AEZs, we randomly selected sublocations (Kenya’s smallest administrative units) as primary sampling units (PSU) and households as secondary sampling units (SSU) based on census data (KNBS, 2010). The number of sublocations per zone was chosen proportionate to the maize area in that zone. In total, we sampled 120 sublocations. In each sublocation, 12 households were randomly selected, except for the coastal lowlands where we selected six households per sublocation due to budget constraints. The survey was conducted between December 2012 and February 2013, referring to the 2012 cropping year. Data were collected on technology adoption and various other farm, farmer, household, and contextual characteristics.

3.2. Descriptive statistics

Table 1 shows descriptive statistics for the variables that we use to explain technology adoption in Kenya. As explained in the previous section, farmers may adopt certain technologies on some of their plots but not on others. We therefore carry out the analysis at the plot level, with farm and household level variables referring to the farms and households that operate the respective plots. The upper part of Table 1 shows adoption rates for the input-intensive and NRM technologies considered in this study. Improved maize seeds, including hybrids and improved OPVs, were adopted on 72% of the plots. Mineral fertilizers were adopted on 54% of the plots. Some of the NRM technologies were also adopted quite widely. On more than 50% of the plots, farmers had constructed terraces, managed crop residues, and used organic manure. On the other hand, zero tillage was practiced on only 11% of the plots during the 2012 cropping year.

Table 1 about here

Variables that we use to explain technology adoption are also shown in Table 1. Plot level characteristics include plot size, ownership status, soil fertility, and slope of the land. Socioeconomic characteristics include age, education, and gender of the farmer. Unlike many other studies that focus on the household head, our human capital variables refer to the person in the household responsible for maize farming decisions, which – in many cases – is the wife of the male household head. We also include farm size (land owned) and total livestock units (TLU) owned as measures of asset ownership, and the number of household members aged 15 years and older as a proxy for family labor availability.

Risk preferences of farmers were elicited through a simple lottery experiment that we conducted during the survey. Each farmer was asked to choose one out of five possible options, each with two events of equal probability but different payoffs. For each individual choice, the amount that farmers won was randomly determined by drawing a stone from a blinded bag. The bag contained five blue and five yellow stones, so the farmers had an equal chance of drawing either color. The choice options and the actual distribution of choices are shown in Table 2. Lower numbered choices indicate risk aversion, while the highest-numbered choice – which is five – represents risk-loving farmers. To normalize farmer's initial wealth and avoid possible financial losses, each farmer was given 50 Kenyan shillings (Ksh) at the beginning of the lottery. Before playing with real money, the experiment was practiced with candies to ensure proper understanding of the rules and procedures.

Table 2 about here

We also use a few institutional variables to explain adoption, such as access to credit for agricultural production purposes and distance to the closest market measured in terms of the walking hours required to reach the market place (Table 1). Furthermore, we include a group membership dummy, capturing farmers' organizational capital and social connectedness, which may play an important role for formal and informal information flows. Many development organizations actually build on farmer groups for their community outreach and training activities.

Climatic shocks and weather extremes can also influence technology adoption behavior. We include drought and floods as explanatory variables in the adoption model. Both variables are measured in terms of the farmer-reported frequency of events during a period of 10 years prior to the survey (2003-2012). Finally, we include dummies for the AEZs into the model, using the lowland tropics as the reference zone. Table 3 shows selected climatic and maize-growing characteristics of the six AEZs. The highland tropics, the moist transitional, and the moist mid altitude zones receive higher levels of rainfall than the other three zones and together account for 75% of Kenya's total maize production. Table 3 also shows the distribution of sample households across the AEZs.

Table 3 about here

4. Technology adoption determinants

4.1. Modeling approach

As the adoption of specific technologies is not independent of other technological choices on the same farm, we employ a multivariate probit (MVP) model that accounts for error term correlation (Marenya and Barrett, 2007). The MVP simultaneously models the influence of a set of explanatory variables on each of the different technologies, while allowing unobserved and unmeasured factors (error terms) to be freely correlated (Lin et al., 2005). Correlation between the different adoption decisions may be due to technological complementarities (positive correlation) or substitutabilities (negative correlation). If such correlation exists, estimates of simple probit models would be biased and inefficient. Our MVP model consists of 7 binary choice equations, namely use of improved maize seeds, mineral fertilizer, terracing, soil bunds, crop residues, zero tillage, and use of animal manure. We therefore have seven dependent binary variables y_i.

$$y_{im}^{*} = \beta_m + X_{im} + \varepsilon_{im} \quad m = 1,2 \ldots .7 \tag{1}$$

$$y_{im} = \begin{pmatrix} 1 \; if \; y_{im}^{*} > 0 \\ 0 \; otherwise \end{pmatrix} \tag{2}$$

where y_{im}^{*} is a latent variable that captures the unobserved preferences associated with the choice of technology m. This latent variable is assumed to be a linear combination of observed characteristics, X_{im}, and unobserved characteristics captured by the stochastic error term, ε_{im}. The vector of parameters to be estimated is denoted by β_m. Given the latent nature of y_{im}^{*}, estimation is based on observable binary variables y_{im}, which indicate whether or not a farmer used a particular technology in the reference year.

The error terms $\varepsilon_{im,\ m=1,2.....7}$ are distributed multivariate normal each with mean 0 and a variance-covariance matrix V, where V has 1 on the leading diagonal, and correlations $p_{jk} = p_{kj}$ as off diagonal elements:

$$\mathrm{V} = \begin{Bmatrix} 1 & p_{12} & p_{13} & . & . & p_{1k} \\ p_{21} & 1 & p_{23} & . & . & p_{2k} \\ p_{31} & p_{32} & 1 & . & . & p_{3k} \\ . & . & . & 1 & . & p_{4k} \\ . & . & . & . & 1 & p_{5k} \\ p_{j1} & p_{j2} & p_{j3} & p_{j4} & p_{j5} & 1 \end{Bmatrix} \tag{3}$$

The computation of the maximum likelihood function based on a multivariate normal distribution requires multidimensional integration. Different simulation methods were proposed to approximate such a function (Train, 2002). The Geweke–Hajivassiliou–Keane (GHK) simulator is a particularly popular choice in empirical research (Geweke et al., 1997; Hajivassiliou et al., 1996). The GHK simulator exploits the fact that a multivariate normal distribution function can be expressed as the product of sequentially conditioned univariate normal distribution functions, which can be accurately evaluated (Cappellari and Jenkins, 2003). We use the GHK approach and employ a simulated maximum likelihood estimator that also offers possibilities of cross-equation tests and restrictions in parameters.

4.2. Estimation results

Table 4 presents results of the MVP adoption model. Based on a likelihood ratio test we reject the null hypothesis of zero correlation between the error terms (p<0.000), so that the MVP is preferred over single-equation probit models. In the Table we report coefficient estimates as well as marginal effects. The marginal effects indicate how each explanatory variables influences the probability of technology adoption. For dummy variables, the marginal effect shows the impact of the variable changing from 0 to 1.

Plot ownership has a significant effect in most equations, but with different signs. Owning the plot increases the probability of adopting stone terraces and soil bunds by 9 and 4 percentage points, respectively. The probability of using manure is also increased by 8 percentage points. In contrast, owning the plot decreases the probability of adopting improved seeds (4 percentage points), mineral fertilizer (9 percentage points), and zero tillage (5 percentage points). The positive effect of plot ownership for some of the NRM technologies is plausible, especially when certain investments are required. If the plot does not belong to the farmer, or if tenure insecurity exists, farmers have little incentive to invest in land-improvement technologies that may increase or sustain productivity in the longer run (Feder et al., 1985). The negative effect of plot ownership for improved seed and mineral fertilizer adoption is less intuitive, but can also be explained. In Kenya, many farmers who grow maize for home consumption do not use mineral fertilizer. These subsistence-oriented farmers grow maize mostly on their own plots. On the other hand, farmers who rent in land for maize production tend to be more commercialized and thus also use more purchased inputs.

Table 4 about here

The size of the plot has a positive effect on adoption of terracing, crop residues, and zero tillage, but a negative effect on the use of manure and soil bunds. As the construction of stone terraces requires significant investments – including certain cost components that are independent of the plot size – adopting this technology on larger plots is more economical. Similarly, zero tillage practices are facilitated with certain mechanization equipment (e.g., direct seeders), so that economies-of-scale occur.

We also find that soil fertility affects the adoption of some of the technologies, yet without a clear pattern between input-intensive and NRM technologies. Among the input-intensive technologies, good soil fertility increases the probability of adopting improved seeds, while it decreases the probability to adopt mineral fertilizer. Among the NRM technologies, good soil fertility has a positive effect on the adoption of stone terraces, and a negative effect on the adoption of soil bunds and zero tillage. The slope of the land does not significantly affect the adoption of improved seeds, but it increases the adoption of several of the other technologies. The adoption of anti-erosion measures such as terracing and zero tillage is more likely on land with steep slopes, which is consistent with findings by Marenya and Barrett (2007). Similarly, the adoption of fertilizer is more likely on steeper slopes, possibly to compensate for nutrient losses through soil erosion.

In terms of the socioeconomic variables, gender of the farmer seems to matter less for the adoption of NRM technologies than for input-intensive technologies, yet the picture is not uniform. Male farmers are more likely to adopt improved seeds, supporting the hypothesis that female farmers have worse access to new technologies. However, for mineral fertilizer the reverse is true: female farmers are more likely to adopt fertilizer. A possible explanation is that women are more constrained in their access to information than in their access to the technology itself (Kabunga et al., 2012). Access to good information is probably more important for the adoption of improved seeds, where new varieties are frequently released, than for mineral fertilizer, where product innovation tends to be less rapid. Farmer age has a positive effect on the adoption of improved seeds, crop residues, and manure, probably because older farmers are more experienced. However, for crop residue management, this effect is diminishing, possibly because very old farmers are less energetic.

Education of the farmer has a positive influence on the adoption of improved seeds and fertilizer. These inputs are relatively easy to use, so this effect is unlikely due to the technologies' complexity. A more plausible explanation is that better-educated farmers have more lucrative income sources and thus fewer capital constraints and higher opportunity costs of time. Education as a proxy for the opportunity cost of time could also explain the negative effect of this variable for some of the NRM technologies, as these technologies tend to be more labor-intensive. Interestingly, household size, which we use as an indicator of family labor availability, is not significant in most of the equations. One exception is fertilizer use, where we observe a negative effect of household size. Larger households seem to substitute family labor for other yield-increasing inputs and vice versa.

The results for the risk attitudes of farmers are somewhat surprising. Usually one would expect that risk aversion leads to lower technology adoption. We observe the reverse for some of the technologies, such as improved seeds, terracing, and crop residue management (remember that higher values of the risk index imply that farmers are more risk-loving). While this is difficult to explain, we can at least conclude that risk aversion as such is not a major constraint for most of the technologies considered here. Farm size plays a significant role for the adoption of some technologies, but again without a clear divide between input-intensive and NRM technologies. Farmers with larger land areas are more likely to adopt improved seeds, zero tillage, and crop residue management, but less likely to adopt soil bunds and manure.

A larger number of livestock units on the farm increase the probability of manure use in maize, but decrease the probability of retaining crop residues in the field. In mixed crop-livestock systems, farmers often use crop residues as animal fodder. Livestock ownership also decreases the probability of mineral fertilizer use, because farmers consider organic manure and mineral fertilizer as substitutes. On the other hand, livestock increases the probability of improved seed adoption, which may be attributed to wealth effects. Similar to farm size, the number of livestock units owned is a wealth indicator, and wealthier farmers are often observed to adopt new seed technologies faster.

In terms of the institutional variables, access to credit facilitates the adoption of several technologies, which is unsurprising. However, the public notion that credit-constrained smallholders would find it easier to adopt NRM instead of input-intensive technologies cannot be confirmed. The reason is that some of the NRM technologies are labor-intensive, so that hired labor may be required. Other complementary inputs that have to be purchased may also play a role for some NRM technologies. For instance, the adoption of conservation agriculture practices is facilitated by the use of chemical herbicides and direct seeder equipment. Distance to market is positively associated with crop residue retention, but negatively associated with the adoption of improved seeds and mineral fertilizer. This is plausible, because market distance contributes to higher transport and transaction costs, so that the use of purchased inputs is less likely in remoter areas. Membership in a farmer group does not seem to affect the adoption of input-intensive technologies, but the adoption of terraces, soil bunds, and manure is positively influenced. This is probably related to different information channels. In Kenya, soil and water conservation techniques are primarily promoted by the government extension system and NGOs that increasingly build on farmers groups for their community outreach and extension activities.

In terms of agro-ecological factors, weather extremes influence technology adoption significantly. Farmers who experienced more frequent droughts and floods in the past are less likely to adopt improved seeds and mineral fertilizer. It is commonly observed that smallholder farmers who operate under erratic weather conditions use fewer purchased inputs to minimize the financial risk. On the other hand, more frequent droughts and floods increase the adoption of stone terraces. Moreover, drought experience makes it more likely that farmers decide to retain crop residues in the field. These technologies help farmers to reduce production risks. As explained above, terraces and mulching are mechanisms to reduce water losses through runoff and evaporation. Soil bunds, in contrast, are less adopted in flood-prone areas, because floods could easily wash away the investment.

Beyond weather extremes, the AEZ dummies indicate that general climatic factors also play a significant role for technology adoption decisions. The lowland tropics, which we use as the base category, receive the lowest amount of rainfall. Improved seeds, mineral fertilizer, and organic manure are adopted more widely in regions with higher average rainfall. This is expected, because more favorable climatic conditions contribute to higher marginal returns to the use of these yield-enhancing inputs. Of course, this could be different for the adoption of drought-tolerant maize varieties, but such varieties are not yet widely available. Higher rainfall is also positively associated with the adoption of stone terraces. On the other hand, we observe lower adoption of zero tillage and crop residue management in AEZ with higher average rainfalls. This makes sense, because these technologies help to better cope with the stress of too little water.

5. Complementarities and tradeoffs

In the previous section, we have analyzed which factors influence the adoption of different input-intensive and NRM technologies. The technologies are not mutually exclusive, that is, adoption of one technology does not mean that other technologies could not be adopted. In this section, we focus more explicitly on complementarities and tradeoffs between the different technologies. To better understand which technologies are adopted in combination, one can look at the correlation matrix from the MVP model, which is shown in Table A1 in the Appendix. A different but related approach is to estimate a probit model for the adoption of each technology, where adoption dummies for all the other technologies are used as right-hand-side variables. Marginal effects of such probit estimates are presented in Table 5. These results should not be interpreted as causal effects. The only purpose is to look at the direction and strength of associations between the different adoption variables.

Table 5 about here

The negative marginal effects in Table 5 indicate that farmers perceive several tradeoffs between certain technologies, or consider these technologies as substitutes. The construction of stone terraces is negatively associated with the use of soil bunds. This is expected, because both technologies serve the same purpose, only that one is more costly and effective than the other. It would not make sense to adopt both in combination. We also observe a negative association between mineral fertilizer and organic manure adoption. This is plausible, because both technologies deliver nutrients to the soil. Nevertheless, organic and mineral fertilizers have different advantages for soil fertility and texture, so that combining both could lead to positive synergies. The estimation results also indicate that terracing is negatively associated with the two components of conservation agriculture, namely zero tillage and crop residues. While terracing is not a substitute for conservation agriculture, we saw in the previous section that these technologies tend to be adopted in different AEZs, terracing more in wetter and conservation agriculture more in drier environments.

There are also a number of positive associations between adoption variables, indicating technological complementarities. The adoption of improved seeds is positively associated with the adoption of mineral fertilizer. The adoption of zero tillage is positively associated with crop residue management. And the construction of stone terraces and soil bunds is positively associated with the use of organic manure. Terraces and soil bunds are also positively associated with mineral fertilizer use, but apart from this relationship, combinations of input-intensive and NRM technologies are rarely observed.

Most of the positive associations occur either among the input-intensive or among the NRM technologies, but not much across these two categories. While this pattern is in line with the public notion that input-intensive and NRM technologies are incompatible, such incompatibility does not actually exist in reality. While NRM technologies can reduce the need for external inputs in situations where these inputs are excessively used, this does not automatically mean that optimal input use is zero when NRM technologies are adopted. Recent research has shown, for instance, that there is complementarity between the adoption of conservation agriculture techniques, improved seeds, and other external inputs (Kassie et al., 2015). This is in line with the results from our MVP model in the previous section. While we found that some technologies are more adopted in certain situations than others, we did not find a clear divide in adoption determinants between input-intensive and NRM technologies.

When there is no incompatibility, what are the reasons that most farmers adopt either input-intensive or NRM technologies rather than a combination of both? We hypothesize that this is partly related to different information flows for the two types of technologies. Figure 1 shows how farmers in our sample learned about different types of technologies. Indeed, significant differences in the sources of information can be observed. For NRM technologies, the government extension service is the most important source of information, followed by radio, other farmers, and NGOs. For improved seeds, the government extension service is also an important source of information, but the proportion of farmers who learn about new seeds from other sources is significantly higher than for NRM technologies. Input traders and companies are important here, whereas they play no role as a source of information for NRM technologies. Radio and TV commercials are also more important for input-intensive technologies. This is not surprising, because private companies market their products in order to increase commercial sales. NGOs, on the other hand, are less important as a source of information for improved seeds and other input-intensive technologies.

One may consider this pattern of information flows as an efficient division of labor. Private companies market their products, whereas the public sector and NGOs focus on the promotion of NRM technologies for which private sector incentives are lower. This divide is also fostered by the bifurcated public debate. Some organizations that promote NRM technologies would not promote the use of external inputs at the same time, because of the perceived incompatibility. Getting information from different sources and then making informed decisions would not be a problem if farmers really had access to the different types of information. However, this is often not the case because of high transaction costs involved in obtaining information. When farmers happen to have access to only one type of information, the picture they get is incomplete, and synergies between different types of technologies cannot be fully exploited. This calls for more balanced extension approaches by all actors involved in farmer outreach activities.

6. Conclusion

We have analyzed the adoption of different input-intensive and NRM technologies among maize farmers in Kenya, using data from a recent nationally representative survey. Most existing adoption studies have either looked at input-intensive technologies or at NRM techniques, using different data and methodologies, so that comparisons were not easily possible. We used a multivariate probit model to address this shortcoming. The input-intensive technologies considered in this study were improved maize seeds and mineral fertilizer. NRM technologies included in the analysis were zero tillage, management of crop residues, organic manure, and the construction of terraces and soil bunds. As explanatory variables we included plot level, farm level, farmer, and household characteristics, as well as contextual factors characterizing infrastructure, institutional, and agroecological conditions. The estimation results show that the adoption determinants differ between technologies. For instance, improved seeds, mineral fertilizer, manure, and stone terraces are more adopted in regions with higher rainfalls, whereas zero tillage and crop residue management are more adopted under drier conditions. Gender, education, farm size, market distance, credit access, and several other variables also play significant roles, partly with differing signs across technologies. However, we did not find a clear divide in terms of adoption determinants between input-intensive and NRM technologies, suggesting that there are certain complementarities between the two types of innovations.

Nevertheless, we found that input-intensive and NRM technologies are rarely adopted in combination. This is due to the fact that the two types of technologies are partly promoted by different organizations. NRM technologies are more promoted by the public extension service and NGOs, whereas for improved seeds and mineral fertilizer the private sector plays a larger role. This divide is fostered by the entrenched public debate about the most appropriate strategies. Many in this public debate consider the use of external inputs and NRM techniques as two incompatible strategies. But this is short-sighted and prevents more widespread implementation of combined approaches that can bring about important synergies. NRM technologies can reduce the use of external inputs in situations where such inputs are excessively used. But this does not imply that optimal input use is zero when NRM technologies are adopted. Especially in the African small farm sector, where little external inputs are used, a combination of improved NRM techniques, better seeds, and increased levels of other inputs could significantly contribute to sustainable productivity growth. This will require more integrated extension and farmer outreach approaches.

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Table 1: Descriptive statistics of adoption and explanatory variables (N=4035)

Variable name	Variable description	Mean	Std. Dev.
Technology adoption dummies			
Improved seeds	=1if seeds are improved varieties, 0 otherwise	0.72	0.45
Fertilizer	=1 if farmer applied chemical fertilizers, 0 otherwise	0.54	0.50
Terraces	=1if farmers practiced terracing on the plot, 0 otherwise	0.52	0.50
Soil bunds	=1 if the farmer had soil bunds on the plot, 0 otherwise	0.17	0.37
Crop residues	=1if farmer left any crop residues on the plot, 0 otherwise	0.54	0.50
Zero tillage	=1if farmer practiced zero tillage on the plot, 0 otherwise	0.11	0.32
Manure	=1 if the farmer used animal manure, 0 otherwise	0.52	0.50
Plot level characteristics			
Plot size	Size of the plot in acres	1.23	1.54
Plot ownership	=1 if farmer owns the plot, 0 if land is rented in	0.88	0.33
Medium soil fertility [a]	=1 if soil fertility was rated medium, 0 otherwise	0.51	0.50
Good soil fertility [a]	=1 if soil fertility was rated good, 0 otherwise	0.37	0.48
Gentle slope [b]	=1 if the slope on the plot is gentle, 0 otherwise	0.43	0.50
Medium slope [b]	=1 if the slope on the plot is medium, 0 otherwise	0.20	0.40
Steep slope [b]	=1 if the slope on the plot is steep, 0 otherwise	0.05	0.22
Socioeconomic characteristics			
Age of farmer	Age of the farmer in years	50.00	14.53
Male	= 1 if the farmer is male, 0 otherwise	0.57	0.50
Education farmer	Years of formal education of the farmer	7.54	3.89
HH size	Number of household members aged >15 years	4.27	1.99
Farm size	Total land owned by the household in acres	5.59	9.11
TLU	Total livestock units	5.85	7.88
Risk loving	Risk attitude of the farmer (discrete scale between 1 and 5); 1 is highly risk averse and 5 is risk loving	3.20	1.45
Institutional variables			
Credit access	=1if the HH has access to credit, 0 otherwise	0.20	0.40
Group membership	=1 if HH participates in any group, 0 otherwise.	0.87	0.33
Market distance	Distance in walking hours to the nearest main market	1.62	1.57
Weather extremes			
Drought	Frequency of drought experienced between 2003-2012	2.21	2.07
Flooding	Frequency of flooding experienced between 2003-2012	0.56	1.73
AEZ dummies			
Dry mid altitude [c]	=1 if HH is located in the dry mid attitude, 0 otherwise.	0.16	0.37
Dry transitional [c]	=1 if HH located in the dry transitional zone, 0 otherwise	0.15	0.36
Moist transitional [c]	=1 if HH located in the moist transitional zone, 0 otherwise	0.26	0.44
High tropics [c]	=1 if HH is located in the high tropics, 0 otherwise	0.18	0.38
Moist mid altitude [c]	=1 if HH is located in the moist mid attitude, 0 otherwise.	0.18	0.38

[a] Base category is poor soil fertility. [b] Base category is flat (no slope). [c] Base category is lowland tropics.

Table 2: Risk attitudes of farmers

Choice	Payoff (Ksh) [a]		Risk preference	Proportion of farmer
	Blue stone (p=0.5)	Yellow stone (p=0.5)		
1	50	50	High risk aversion	19.9%
2	80	30	Moderate risk aversion	7.6%
3	100	20	Low risk averse	31.4%
4	120	10	Risk neutral	17.9%
5	150	-20	Risk loving	23.2%

[a] 10 Kenyan Shilling (Ksh) = 0.012 US Dollars (official exchange rate in early 2014).

Table 3: Characteristics of maize agroecological zones in Kenya

Attribute	Highland tropics	Moist transitional	Moist mid altitude	Dry transitional	Dry mid altitude	Lowland tropics
Elevation (meters)	1600-2900	1200-2000	1100-1500	1100-1700	700-1400	<700
Annual rainfall(mm)	>1800	1000-1800	800-1200	<800	400-800	400-1400
Average temperature (°C)	15.2	19.7	22.1	19.7	22	25.5
Maize area (‘000 ha)	307	461	118	118	118	33
Share of national maize production (%)	35	20	20	10	10	5
Potential yield (t/ha)	6.7	5.2	5.2	4.5	2.7	3.3
Actual yield (t/ha)	2.0	0.7	1.1	1.1	0.5	1.0
Share of households surveyed (%)	18	26	18	15	16	9

Source: Adapted from Hassan (1998) and Jaetzold et al. (2005).

Table 4: Results of the multivariate probit model

	Improved seeds			Fertilizer			Terraces			Soil bunds		
	Coefficient	Std Error	Marginal effects	Coefficient	Std Error	Marginal effects	Coefficient	Std Error	Marginal effects	Coefficient	Std Error	Marginal effects
Plot level characteristics												
Plot size	0.032	0.020	0.009	-0.022	0.017	-0.006	0.043***	0.016	0.014	-0.039**	0.019	-0.009
Plot ownership	-0.127*	0.076	-0.036	-0.289***	0.073	-0.085	0.285***	0.067	0.094	0.167**	0.076	0.040
Medium soil fertility	0.194***	0.070	0.056	0.017	0.072	0.005	0.174**	0.069	0.057	-0.043	0.076	-0.010
Good soil fertility	0.367***	0.075	0.105	-0.168**	0.075	-0.050	0.149**	0.072	0.049	-0.272***	0.081	-0.065
Gentle slope	0.036	0.054	0.010	0.082	0.053	0.024	0.549***	0.05	0.181	-0.135**	0.057	-0.032
Medium slope	0.088	0.067	0.025	0.341***	0.065	0.100	0.899***	0.063	0.296	-0.066	0.069	-0.016
Steep slope	0.12	0.116	0.034	0.662***	0.117	0.196	1.083***	0.119	0.356	0.1	0.116	0.023
socio economic characteristics												
Male	0.114**	0.05	0.033	-0.126**	0.049	-0.037	0.067	0.047	0.022	0.150***	0.053	0.036
Age of farmer	0.019**	0.01	0.005	-0.003	0.010	-0.001	0.003	0.009	0.000	0.006	0.011	0.001
Age of farmer SQ	0.000	0.000	-3.8e-5	1.12e-4	0.000	3.3e-5	3.6e-5	0.000	1e-05	-4.42e-05	0.000	-1.1e-5
Education farmer	0.043***	0.007	0.012	0.070***	0.007	0.021	0.011	0.006	0.003	0.014*	0.007	0.003
Land size	0.009**	0.004	0.003	0.002	0.003	0.000	-0.001	0.003	-0.000	-0.010**	0.004	-0.002
TLU	0.011***	0.004	0.003	-0.012***	0.003	-0.003	-0.002	0.003	-0.001	0.001	0.004	0.000
Risk taking	-0.043***	0.016	-0.012	-0.006	0.016	-0.002	-0.071***	0.016	-0.023	0.036**	0.018	0.009
HH size	-0.015	0.013	-0.004	-0.024**	0.012	-0.007	-0.022*	0.012	-0.007	-0.003	0.014	-0.001
Institutional variables												
Group membership	0.077	0.072	0.022	0.076	0.074	0.023	0.214***	0.069	0.070	0.158**	0.080	0.038
Distance market	-0.038***	0.014	-0.011	-0.025*	0.014	-0.007	0.022	0.014	0.007	-0.008	0.016	-0.002
Credit	0.175***	0.059	0.05	0.276***	0.057	0.082	-0.015	0.053	-0.005	0.142**	0.059	0.034
Climatic shocks												
Drought	-0.028**	0.011	-0.008	-0.091***	0.012	-0.026	0.019*	0.011	0.006	-0.027**	0.013	-0.006
Flooding	-0.015	0.013	-0.004	0.016	0.013	0.005	0.039***	0.012	0.013	-0.056***	0.016	-0.013
AEZ												
Dry Mid altitude	-0.166*	0.097	-0.048	-0.053	0.109	-0.016	1.157***	0.101	0.380	0.044	0.115	0.010
Dry transitional	0.248**	0.099	0.071	0.905***	0.107	0.268	1.174***	0.103	0.385	-0.118	0.118	-0.028
Moist transitional	0.823***	0.105	0.236	1.431***	0.109	0.423	0.416***	0.102	0.137	0.143	0.115	0.034
High tropics	0.882***	0.122	0.253	1.670***	0.122	0.494	-0.026	0.112	-0.008	0.496***	0.123	0.119
Moist mid altitude	-0.361***	0.099	-0.103	0.363***	0.107	0.107	0.373***	0.103	0.123	-0.179	0.119	-0.043
Constant	-0.615**	0.262		-0.793***	0.272		-1.662***	0.262		-1.428***	0.298	

	Crop residues			Zero tillage			Manure		
	Coefficient	Std. error	Marginal effects	Coefficient	Std. error	Marginal effects	Coefficient	Std. error	Marginal effects
Plot level characteristics									
Plot size	0.083***	0.018	0.024	0.045***	0.017	0.013	-0.060***	0.016	-0.017
Plot ownership	-0.079	0.069	-0.023	-0.157*	0.081	-0.045	0.274***	0.065	0.078
Medium soil fertility	0.073	0.074	0.021	-0.376***	0.082	-0.108	0.062	0.067	0.018
Good soil fertility	0.086	0.076	0.025	-0.251***	0.085	-0.072	-0.067	0.069	-0.019
Gentle slope	0.104**	0.053	0.030	-0.053	0.065	-0.015	0.119**	0.049	0.034
Medium slope	0.106*	0.064	0.030	-0.044	0.082	-0.013	0.091	0.060	0.026
Steep slope	0.018	0.109	0.005	0.686***	0.118	0.197	-0.061	0.101	-0.017
Socioeconomic characteristics									
Male	-0.037	0.048	-0.011	-0.034	0.060	-0.010	-0.028	0.045	-0.008
Age of farmer	0.028***	0.010	0.008	-0.001	0.012	0.000	0.021**	0.009	0.006
Age squared	-3.8e-4***	0.000	-1.1e-4	-3.5e-5	0.000	-9.9e-6	-0.001	0.000	-2.9e-5
Education farmer	-0.0126*	0.007	-0.004	-0.017**	0.008	0.000	-0.003	0.006	-0.001
Farm size	0.011***	0.003	0.003	0.010***	0.003	0.003	-0.012***	0.003	-0.003
TLU	-0.010***	0.003	-0.003	0.009***	0.003	0.003	0.017***	0.003	0.005
Risk loving	-0.044***	0.016	-0.013	0.003	0.02	0.001	0.02	0.015	0.006
HH size	0.004	0.012	0.001	0.007	0.015	0.002	-0.038	0.011	-0.011
Institutional variables									
Group membership	0.037	0.071	0.011	0.016	0.086	0.005	0.286***	0.066	0.082
Market distance	0.030**	0.015	0.009	-0.007	0.017	-0.002	-0.035***	0.014	-0.010
Credit access	0.164***	0.055	0.047	0.157**	0.068	0.045	-0.123**	0.051	-0.035
Weather extremes									
Drought	0.036***	0.011	0.010	0.008	0.014	0.002	-0.017	0.011	-0.005
Flooding	0.015	0.014	0.010	0.002	0.015	0.001	-0.017	0.012	-0.005
AEZ									
Dry mid altitude	-1.917***	0.122	-0.550	-0.478***	0.113	-0.137	0.674***	0.096	0.193
Dry transitional	-1.965***	0.124	-0.563	-0.809***	0.125	-0.232	0.576***	0.097	0.165
Moist transitional	-0.883***	0.123	-0.253	-0.279**	0.113	-0.080	0.073	0.098	0.021
High tropics	-0.920***	0.131	-0.264	-0.254**	0.124	-0.073	0.027	0.107	0.008
Moist mid altitude	-0.127	0.127	-0.036	-0.473***	0.116	-0.136	0.220**	0.098	0.063
Constant	0.737***	0.278		-0.414	0.325		-1.269***	0.249	

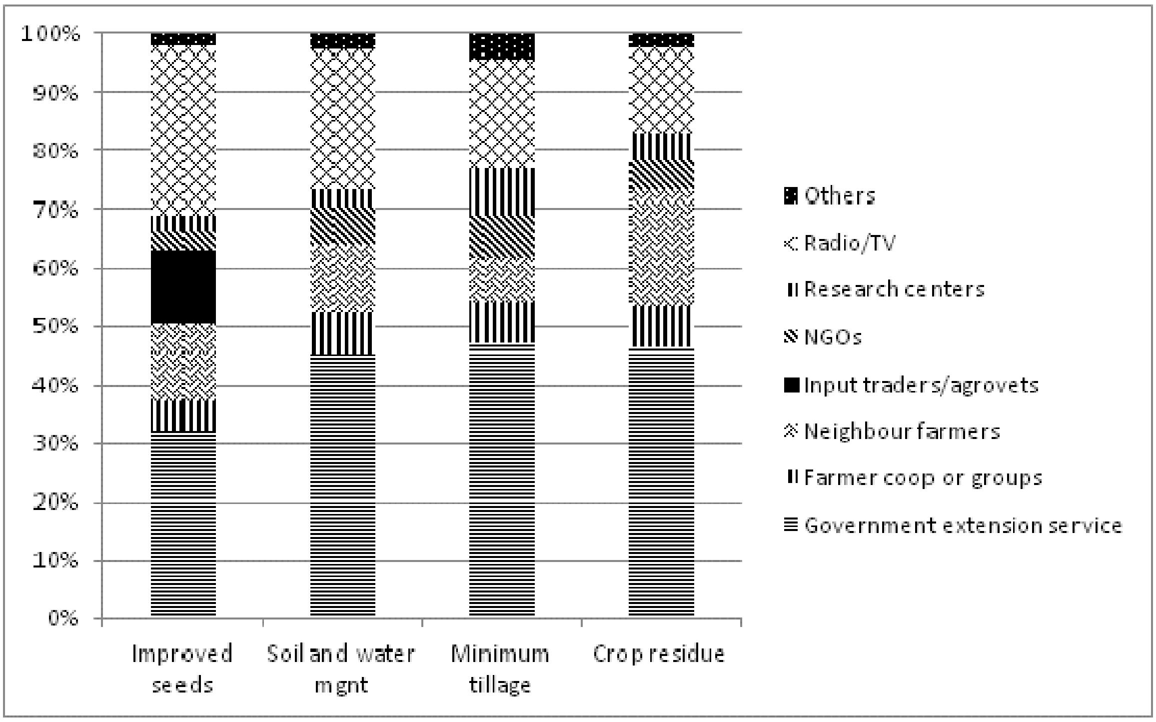
Notes: N=4035; log likelihood = -11772.70; Wald chi^2 = 4169.45; likelihood ratio test of rho chi^2 (21) = 662.488. ***, **, * significant at 1%, 5%, and 10% level, respectively.

Table 5: Simple probit models showing relationships between technologies

	Improved seeds	Fertilizers	Terraces	Soil bunds	Crop residues	Zero tillage	Manure
Improved seeds		0.351***	0.010	0.021*	-0.009	-0.003	0.030
		(0.016)	(0.019)	(0.012)	(0.019)	(0.012)	(0.019)
Fertilizers	0.284***		0.040**	0.024**	-0.030*	0.006	-0.086***
	(0.014)		(0.017)	(0.012)	(0.017)	(0.010)	(0.017)
Terraces	0.007	0.040**		-0.225***	-0.162***	-0.020*	0.109***
	(0.015)	(0.017)		(0.012)	(0.017)	(0.010)	(0.017)
Soil bunds	0.029	0.048**	-0.402***		-0.011	0.019	0.111***
	(0.019)	(0.023)	(0.017)		(0.023)	(0.014)	(0.022)
Crop residues	-0.006	-0.030*	-0.159***	-0.003		0.051***	-0.142***
	(0.015)	(0.017)	(0.016)	(0.011)		(0.010)	(0.016)
Zero tillage	-0.004	0.015	-0.054**	0.029	0.131***		-0.032
	(0.023)	(0.026)	(0.027)	(0.019)	(0.024)		(0.026)
Manure	0.023	-0.084***	0.107***	0.057***	-0.141***	-0.012	
	(0.015)	(0.017)	(0.017)	(0.011)	(0.016)	(0.010)	

Notes: Marginal effects are shown with standard errors in parentheses. N= 4035. ***, **, * significant at 1%, 5%, and 10% level, respectively.

Figure 1: Farmers' sources of information for different technologies (proportions)



Note: Based on a chi-squared test the null hypothesis of equal proportions across technologies is rejected (*p*=0.000).

Appendix

Table A1: Correlation matrix from the MVP model

	Improved seeds	Fertilizer	Terraces	Soil bunds	Crop residues	Zero tillage	Manure
Improved seeds	1						
Fertilizer	0.382***	1					
	(0.028)						
Terraces	0.057*	0.153***	1				
	(0.030)	(0.029)					
Soil bunds	-0.015	-0.071**	-0.595***	1			
	(0.036)	(0.033)	(0.024)				
Crop residues	-0.018	-0.065**	-0.051*	0.113***	1		
	(0.031)	(0.030)	(0.029)	(0.032)			
Zero tillage	-0.033	0.024	-0.058	0.096**	0.142***	1	
	(0.039)	(0.039)	(0.036)	(0.039)	(0.038)		
Manure	0.084***	-0.055*	0.048*	0.087***	-0.101***	-0.004	1
	(0.029)	(0.028)	(0.027)	(0.030)	(0.028)	(0.034)	

Note: Numbers in parenthesis are *p*-values. The likelihood ratio test of equal correlation coefficients is rejected ($p < 0.000$). N= 4035. ***, **, * significant at 1%, 5%, and 10% level, respectively.