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Impact of Improved Farm Technologies on Yields

The Case of Improved Maize Varieties and Inorganic Fertilizer in Kenya

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Abstract

This study investigates the impact of package adoption of inorganic fertilizers and improved maize seed varieties on yield among smallholder households in Kenya. We used a quasi-experimental difference-in-differences approach combined with propensity score matching to control for both time-invariant and unobservable household heterogeneity. Our findings show that inorganic fertilizers and improved maize varieties significantly increase maize yields when adopted as a package, rather than as individual elements. The impact is greater at the lower end of the yield distribution than at the upper end. A positive effect of partial adoption is experienced only in the lower quartile of yield distribution. The policy implication is that complementary agricultural technologies should be promoted as a package, and should target households and areas experiencing low yields.

Key Words: technology adoption, yield, difference-in-differences, Kenya

JL Codes: Q12, Q16, O33, O55

Contents

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Introduction

[Using household-level plot data, this study applies a difference-in-differences approach to evaluate the impact of adopting a package of improved seeds and fertilizer, compared to partial adoption or non-adoption, on maize yield in Kenya. For most sub-Saharan African countries, the adoption of sustainable agricultural practices that enhance agricultural productivity and improve environmental outcomes remains the most pragmatic option for achieving economic growth, food security and poverty alleviation. This underscores the role of agricultural research and technological improvements, in particular, research that targets smallholder households, the environments within which they operate, and their most common crops. However, mere research and technology development is inadequate because its adoption may be totally absent, partial or even reversed due to disadoption. The relationship between technology adoption and agricultural productivity is, however, a complex one that is influenced and shaped by farm and farmer characteristics, access to extension and financial services, risk preferences, social capital, and farm size, among other factors (Barrett et al. 2005; Foster and Rosenzweig 1995).

Maize is vital for global food security and poverty reduction. In Africa, maize is the most widely grown staple crop and is rapidly expanding to Asia. Due to the increasing demand for feed and bio-energy, the demand for maize is growing and is expected to double by 2050 (Rosegrant et al. 2007). Unfortunately for many farmers in Africa, maize yields (output per acre) have fallen in the last decade, in spite of improvements in agricultural technologies (Suri 2011). This is further complicated by the threat of climate change, which will make it more difficult to meet the growing demand for maize (Rosegrant et al. 2009). This is worrisome for economic and social policies aimed at increasing food production and agricultural incomes.

Understanding persistently low technology adoption and its impact in the maize sector motivates our interest in this study. Field trials at agricultural stations across Kenya have

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developed high-yielding seed varieties, optimal fertilizer application rates and increased farmer field days as demonstration projects (see Karanja 1996; Duflo et al. 2008). Despite this, adoption rates of improved maize varieties and fertilizers remain low. This is in sharp contrast to other countries such as the United States that have fully adopted high yielding varieties (HYV), (Dorfman 1996). In spite of the higher productivity of certified seed and fertilizer relative to other practices, small scale farmers are seen to be slow in adoption. Many attempts have been made to investigate the reasons for the partial adoption, but few have studied the subsequent impact of packaged multiple technologies. An attempt to establish whether a technology yields high returns and thus merits promotion faces several fundamental challenges. First, there is over-reliance on field station trials in which labour, fertilizer use and other inputs are very carefully controlled. Yet, it is difficult to approximate *ex post* how these variables operate under prevailing farmer conditions. Farmers face many constraints that affect their adoption decisions. Hence, establishing the actual gains attributable to a particular technology poses methodological difficulties. Second, past research has put too much emphasis on single technologies. Yet, farmers are observed to practice various combinations of multiple technologies in light of their binding constraints. Last, historical context and policy antecedents influence contemporary technology adoption decisions. For instance, fertilizer application demands high levels of information and knowledge. Thus, the individual farmer may at first suffer low pay-offs before she benefits from the knowledge she has gained. This implies that the value of adoption would increase with time as more farmers gain experience with the technology. This is, of course, true for accumulated experience in choosing fertilizer type and dosage for various crops. Analysis of technology impacts without controlling for this path dependence may either overestimate or underestimate the influence of various technologies.

We find that inorganic fertilizers and improved maize varieties improve yields. The magnitude of the effect of these technologies on yield, however, depends on whether a farm household adopts a complete package, and on the current yield levels. Adoption of the complete package of technologies (planting fertilizer, improved maize varieties and top dressing fertilizer) dominates both partial adoption and non-adoption. These effects are largest among households falling within the lower quantile of the yield distribution (25th and 50th quantiles). Partial adopters are better off than non-adopters only at the lower end of yield distribution (25th quantile). At the 75th quantile, this trend is reversed. We find that, with increased efficiency, the effect of inorganic fertilizers and improved maize varieties on maize yield becomes larger.

The present study examines the impact of adopting certified seed practices and fertilizer as a package on yield by maize farmers in Kenya. The objective is to determine the yield differences between adopters and non-adopters of improved maize varieties and inorganic fertilizers. Substantial gaps in knowledge exist as to the productivity impacts of the package adoption decisions. Hence, a need exists for establishing the productivity impact of the package adoption of certified maize and fertilizers. Evaluation studies of this nature have been limited, perhaps constrained by lack of appropriate data. Most of the previous studies have relied on experimental data, yet farmers do not operate under controlled conditions, and therefore results from experiment stations are unlikely to be replicated in farmers' fields. Thus, using household plot-level panel data, this study was able to control for the confounding factors and provide empirical evidence on the effect of improved maize varieties and inorganic fertilizer on crop yield in Kenya's smallholder crop agriculture. Our empirical analysis uses a unique national panel data set. All geographic regions of the country are covered; the data includes household information, input use, sources of information, distance to input markets, etc.

The knowledge and information generated may be useful in rectifying the situation and giving a boost to the region's maize sector. Better understanding of the impact will help redress the policy failures experienced thus far with technology adoption in the region. We contribute to the growing literature on the impact of adopting multiple technologies in maize production among smallholder farmers. Additionally, we provide a micro-perspective on the effect of improved maize varieties and inorganic fertilizer on smallholder land productivity. The findings are important for providing feedback to agricultural technology development research and offering evidence to policy makers and technology disseminators on the results of the technologies under practical conditions in farmers' fields.

The remainder of the article is organized as follows. The next section discusses the literature on inorganic fertilizer and improved maize varieties and how they affect yields; the following section discusses the challenges of estimating the impact of improved technologies on crop yield before exploring the estimation strategy used. Data used in the analysis are described in the fourth section and results are discussed in the fifth section. The final section concludes and provides policy implications.

Inorganic Fertilizer, Improved Maize Varieties and Productivity

Previous studies on agricultural technology adoption have long emphasized how heterogeneity in farm and farmer characteristics shape adoption decisions, with scant attention paid to the multiple nature of the decisions (Feder, Just and Zilberman 1985). Standard empirical models used to study technology adoption treat farmer demand as a multinomial logit, as a binary comparison of utility, or as returns to a particular technology alternative, such as certified seeds versus traditional seeds. They failed to capture the impact of multiple adoption of various technologies in farmer adoption decisions. Drawing on literature in Kenya, Gerhart (1975) simply looked at adoption of hybrid maize in western Kenya. Rapid diffusion was attributed to relieving constraints such as credit availability, extension services, education, risk and fertilizer. A number of other papers focus on credit constraints (see Croppenstedt et al. (2003), looking at Ethiopia, and Salasya et al. (1998) for Western Kenya). Ouma et al. (2002) provided evidence from Embu County in Kenya, in which they show that gender, agro-climatic zone, manure use, hire of labour and extension services were significant determinants of improved seed and fertilizer. There is no mention of yield. Wekesa et al. (2003) studied the adoption of several hybrids and fertilizer in the coastal lowlands of Kenya and found low use, which was attributed to non-availability and high cost of seed, unfavourable climatic conditions, perception of insufficient soil fertility, and lack of money.

In field experiments to determine the optimal amount of fertilizer use, the Fertilizer Use Recommendation Project (FURP) studied 70 sites across the country in the early 1990s in conjunction with the Kenya Maize Database Project (MDBP). In the same vein, a number of field trials at Kenya Agricultural Research Institute (KARI) sites were conducted. There were large increases in yields from hybrid seed and fertilizer at KARI trials, while FURP recorded yields about half of those by KARI (KARI 1993). Hassan et al. (1998) report higher adoption and diffusion rates of hybrid seeds, but only for high potential areas, and attribute poor results in marginal areas to poor extension services and seed distribution. In another study, Hassan et al. (1998) report less than the recommended fertilizer application, which leads to a 30% yield gap between farmers' fields and the experimental stations.

Dercon and Christiaensen (2007) find that poor harvest and subsequently low consumption could lead to low fertilizer application in Ethiopia. The results are similar to those of neighbouring Kenya, where adoption patterns also vary from season to season. Duflo et al. (2008) sought to understand the returns to fertilizer and reasons for low fertilizer application in Western Kenya using experiments. They found dismal learning effects and a rate of return to top dressing fertilizer of between 52% and 85%. In addition, they initiated a Savings and Fertilizer Initiative (SAFI), which offered farmers subsidized fertilizer at harvest time as opposed to planting time. They reported an 11-14% increase in adoption. More recently, Duflo et al. (2011) concluded that behavioural biases prevent farmers from attaining their intentions to use fertilizer. They recommended providing fertilizers immediately after harvest, when farmers have cash from crop sales, rather than later in the planting season.

De Groote et al. (2005), using an econometric approach, analysed the maize green revolution in Kenya using farm level surveys between 1992 and 2002. They found that intensity of fertilizer use had a major effect on maize yield. However, the use of improved maize varieties did not have any effects on the yields, an indication that some local varieties could perform as well as the improved varieties in some areas. The yield-enhancing effects of fertilizer and improved maize varieties are confirmed by Owino (2010), who used experimental data in the Trans Nzoia District. Owino further noted that the yields vary with different improved varieties, fertilizer types and intensity, and management practices.

Beyond Kenya, De Groote et al. (2003) conducted an impact assessment of the Insect Resistant Maize for Africa (IRMA) project using an experimental approach and realized that this maize variety would lead to about a 14 percent rise in yields due to reduced harm from the stem borer. Morris et al. (1999) applied the qualitative approach to evaluate the performance of improved maize varieties in Ghana, under the grains development project. They found that improved maize varieties significantly increased yields for farmers switching from local varieties. The yield increase would be even higher if the farmers applied fertilizer on the improved varieties. This indicates that the improved varieties perform better under an improved management system, although they still perform better than the local varieties even if the farmers do not use improved management approaches. Use of fertilizer alone was also observed to increase yields significantly, even where the farmers planted local maize varieties. The main limitation of the study by Morris et al. (1999) is that it relied on recollections by farmers who had switched from one variety to another. This may reduce the reliability of the results, especially for farmers facing multiple scenarios. The positive effect of improved maize varieties on yield has also been noted in Mexico (Becerril and Abdulai 2010; Bellon and Hellin 2010) and other countries of Africa (Alene et al. 2009).

Marenya and Barrett (2009), in an interesting study of fertilizer interventions in Western Kenya, find that fertilizer application is beneficial to farmers with high soil organic matter (SOM). The implication is that plots with poor, degraded soils limit the marginal productivity of fertilizer. The finding suggests that fertilizer interventions are not very helpful for poorer farmers who largely cultivate soils deficient in SOM. Suri (2011), using a dataset similar to ours, also found that not all farmers benefit from fertilizer use, despite the presence of high average returns. These findings challenge conventional wisdom and call for further work, especially among the poor who require multiple inputs in response to a new technology. Understanding the distribution of yield as a result of the use of multiple technologies is important for policy design. This approach is especially important for understanding the results of new technologies on farms that are actually worked by farmers, which is a different situation than evaluating results in highly monitored field experimental plots.

Impact Evaluation Challenges and Estimation Strategy

Theoretical justification may drive the belief that improved maize varieties and inorganic fertilizers increase maize yields. However, isolating the contribution of these improved technologies to productivity is not an easy undertaking. How can we be sure that the yield differences between adopters and non-adopters of improved maize varieties, inorganic fertilizers, or both are due to adoption of these technologies? With experimental data, we would have the counterfactual information on which to base the causal inference. But without experimental data, the researcher would have to contend with two potential problems. The first problem is self-selection, which arises because households decide whether to adopt the improved maize varieties and inorganic fertilizers based in part on their expectation of the benefits. The second problem is related: farm households could be systematically different in their demands for the improved maize varieties and inorganic fertilizers. Therefore, unobservable characteristics of farmers and their farms may affect both the adoption decision and the productivity outcome. Thus, evaluation must account for both heterogeneity of the farm households and endogeneity of adoption of improved maize varieties and inorganic fertilizers.

This study used Difference-in-Differences (DID) as suggested by Smith and Todd (2005). DID controls for the endogeneity of adoption of improved maize varieties and inorganic fertilizers among the farm households arising from unobserved fixed effects. This provides consistent estimates of the impact of improved maize varieties and inorganic fertilizers on maize yields (Abadie 2005).

For this study, the DID estimator is the difference in average maize yield among the adopters of improved maize varieties and inorganic fertilizers between the baseline and follow-up periods, minus the difference in average yield among the non-adopters for the same periods. It is derived from the difference of the first difference (FD) estimators of the two groups. The two-period panel data FD estimator is specified as follows:

$$Y_{i1} = \delta_0 + \gamma_1 X_{i1} + \phi_i + \varepsilon_{i1} \tag{1}$$

$$Y_{i2} = (\delta_0 + \alpha) + \gamma_2 X_{i2} + \phi_i + \varepsilon_{i2} \tag{2}$$

Subtracting (1) from (2) yields:

$$\Delta Y_i = \alpha + \gamma \Delta X_i + \Delta \varepsilon_i , \tag{3}$$

where Y_i is the maize yield, X_i is a vector of exogenous variables, ε_i is the error term and Δ is the differencing operator. The unobserved effect, ϕ_i, has been differenced away (which is the main advantage of this approach because the assumption that ϕ_i is uncorrelated with X_{it} is no longer necessary). This implies that time-invariant unobserved heterogeneity is no longer a problem in the analysis of the effect of adoption of improved maize varieties and inorganic fertilizers on maize yield. α measures the change in intercept while γ is the coefficient of change in independent variables between the two periods. Equation 3 is computed for both the adopters and the non-adopters of improved farm technologies. Consequently, DID is computed as:

$$DID = FD_A - FD_{NA} , \tag{4}$$

where FD_A is the maize yield change for the adopters of improved maize varieties and inorganic fertilizers between the baseline period and the follow-up period, while FD_{NA} is the yield change for the non-adopters for the same periods.

The DID approach has the advantage of capturing variations over time by estimating time-varying parameters (Abadie 2005). However, the assumption of equal trends between adopters and non-adopters must be satisfied in order to obtain unbiased and valid estimates. Moreover, the approach is not able to eliminate time-varying unobserved heterogeneity. As a result, this study tests for the “equal trends” assumption and also combines DID with Propensity Score Matching (PSM). PSM resolves potential sources of selection bias that DID is unable to deal with by restricting the analysis only to the adopting households that are suitably matched with non-adopting households on observable characteristics.

Other approaches that have previously been used to address the problem include: the Heckman two-step method, which is based on a strong assumption of normality of distribution of the unobserved variables and linearity of the conditional expectation of ε_{it} given μ_{it} (Olsen 1980); and the Instrumental Variable (IV) approach, which imposes a linear functional form assumption. Linearity assumption implies that coefficients of control variables are similar for adopters and non-adopters, an assumption which is unlikely to hold (Jalan and Ravallion 2003; Mendola 2007). This is because technology adoption would also lead to increased productivity of other factors of production (Alene and Manyong 2007). A fixed effect procedure (Crost et al. 2007) and an endogenous switching regression (Maddala 1983) may also be used.

Two technologies/innovations – inorganic fertilizers and improved maize varieties and their combinations – were used for this analysis.

Data and Descriptive Statistics

The data used in this study are part of the Tegemeo Institute panel data on agricultural households in Kenya. It covers all parts of the country except Nairobi and the North Eastern provinces, which are not extensively used for crop production.

The agricultural technologies of interest are broadly improved maize varieties and inorganic fertilizer. To understand how the farm households combine the technologies, inorganic fertilizer is further divided into planting and top dressing fertilizer. The study considers joint adoption of improved maize varieties, planting fertilizer and top dressing fertilizer as a complete package. Other combinations are classified as partial adoption and include planting fertilizer with certified seed, planting fertilizer with top dressing fertilizer, planting fertilizer only, certified seed only and top dressing fertilizer only.

Summary statistics indicate that most adopters opted for either the complete package or planting fertilizer with certified seed in the periods of reference. Table 1 provides these statistics.

Table 1. Summary statistics: technologies adopted by households

Technology	Percentage of adopters	
	2004	2007
Package	23	25
Planting & top dressing	4	5
Planting fertilizer only	6	7
Top dressing fertilizer only	2	1
Certified maize seed only	11	13
Planting fertilizer & seed	26	27

These statistics show that the only partial adoption that is popular is that of planting fertilizer and certified maize seed, which ranks even higher than the complete package adoption. Other categories of partial adoption have very low preference among the farm households. Attempting to analyse their effects on maize yield may not yield any meaningful results. Consequently, the study broadly uses package adoption and partial adoption. Partial adoption is taken as anything less than the full package. Output variation is compared between:

a) Package adopters and non-adopters; and

b) Partial adopters and non-adopters.

This approach also enables comparison of the performance of the package adopters and that of the partial adopters.

The 2004 survey was used as the baseline, while the 2007 survey was the follow-up. Table 2 summarizes yield and the covariates in addition to technology adoption that are likely to affect yield.

Table 2. Summary statistics of the variables used in the analysis of yield differences among adopters and non-adopters of farm technologies

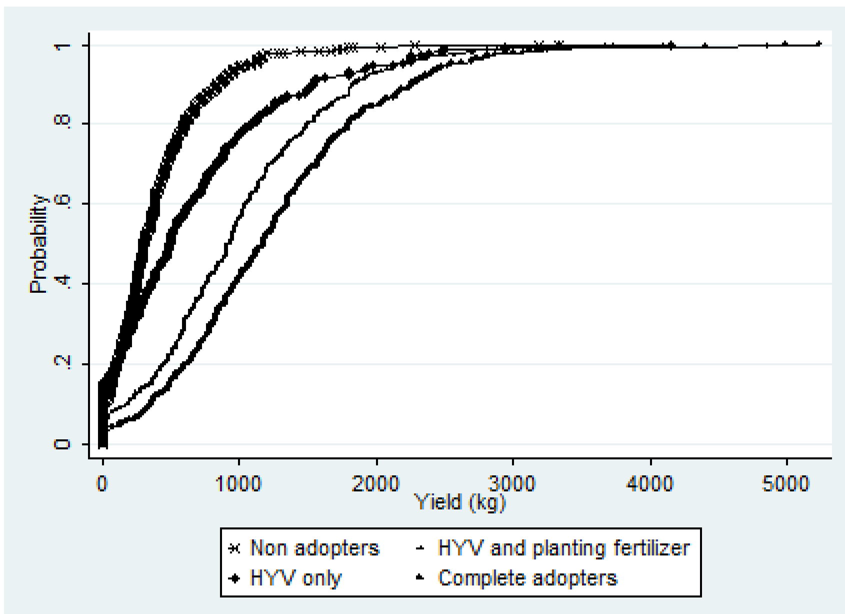
Variable	Package				Planting fertilizer and certified seed			
	2004		2007		2004		2007	
	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Yield (kg)	2,320 (3,928)	882 (1,712)	3,867 (12,549)	876 (1,434)	1,395 (2,108)	1,151 (2,598)	1,325 (1,996)	1,750 (7,579)
Mid-high altitude	0.99	0.87	0.99	0.86	0.99	0.87	0.99	0.86
Well-drained soils	0.85	0.79	0.80	0.79	0.87	0.76	0.91	0.76
Manure/acres(kg)	544 (1,238)	625 (1,292)	475 (1,207)	575 (1,081)	724 (1,485)	566 (1,199)	657 (1,302)	511 (1,037)
Mechanized farms	0.58	0.47	0.62	0.43	0.57	0.47	0.47	0.48
Age of head (years)	53	53	55	53	54 (18)	53 (21)	53 (23)	53 (23)
With post-primary education	0.44	0.21	0.38	0.21	0.28	0.26	0.26	0.25
Male heads	0.86	0.77	0.86	0.73	0.83	0.78	0.76	0.75
Non-crop income	122,276 (141,065)	99,480 (182,920)	152,784 (301,468)	110,288 (193,780)	114,243 (209,965)	101,460 (160,306)	123,902 (234,437)	120,086 (223,977)

Wage rate for farm workers (Ksh/day)	76 (30)	85 (37)	84 (26)	90 (32)	85 (30)	83 (37)	93 (29)	87 (31)
Received credit	0.36	0.27	0.23	0.25	0.40	0.25	0.26	0.24
Participating in social groups	0.75	0.74	0.70	0.76	0.77	0.73	0.78	0.73
Distance to market	6.7 (7.4)	6.5 (7.2)	7.3 (7.6)	6.3 (7.1)	5.4 (4.9)	6.9 (7.9)	5.4 (4.6)	7 (8)
Ratio of male	0.40	0.34	0.49	0.40	0.42	0.33	0.45	0.42
Household size	4 (2)	4 (2)	6 (3)	5 (3)	4 (2)	4 (2)	5 (3)	6 (3)
Expected yield	1,146 (359)	618 (334)	1,279 (318)	705 (287)	869 (291)	695 (430)	927 (261)	824 (420)
Yield variability	478,620 (583,744)	345,963 (593,159)	492,007 (574,992)	315,364 (415,824)	475,068 (801,358)	342,602 (498,317)	365,808 (557,126)	358,325 (430,960)

Standard deviations in parenthese

A cursory examination of the summary statistics reveals that adopters and non-adopters of the two farm technologies differ remarkably in yield, intensity of manure application, non-crop income, education, expected yield and yield variability. The yields were highest among the adopters of the complete package in 2004. Overall, adopters of the complete package dominated their non-adopter counterparts in both periods. Partial adopters dominated their non-adopter counterparts. This is more clearly revealed by the first-order stochastic dominance plot (Figure1).

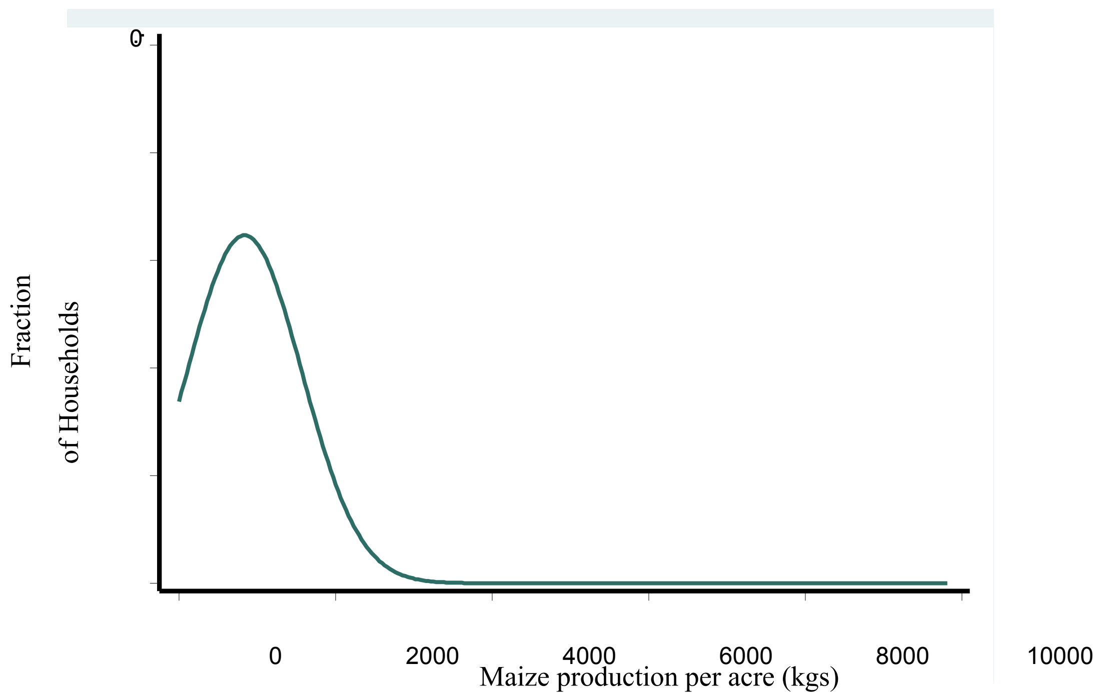
Figure 1. Average Maize Yield per Acre by Farm Technology



Adopters of the complete package dominate partial adopters (high yielding maize varieties and planting fertilizer, and high yielding maize varieties only) and non-adopters. This is shown by the maize yield cumulative distribution function (CDF) for the different technology adopter categories. While these differences may not be interpreted as impacts, they provide an indication that there may be structural differences in maize yield among adopters of the complete technology package, partial adopters and non-adopters. These differences are, however, less pronounced at the lower and the upper end of the maize yield distribution.

A test of the distribution of the maize yield indicates that there is heavy skewness to the left (Figure2).

Figure 2. Distribution of Maize Yield (kg) Among Kenya's Smallholders



This kind of distribution makes regression based on the mean less reliable and less informative (Koenker and Hallock 2001). To overcome this challenge, the study used quantile regression. Quantile regression allows analysis of the impact of adoption of the different farm technologies on maize yield among the smallholder farm households based on sub-sets of unconditional yield distribution. This way, the covariates are allowed to influence location, scale and shape of the maize yield distribution (Koenker and Hallock 2001).

Manure application was lower among the adopters than the non-adopters of the complete package throughout the period of reference, although the intensity declined for both groups in 2007. Among the partial adopters, the adopters dominated the non-adopters in manure application. The intensity of manure application dropped again in 2007. Complete package adopters increased the intensity of planting fertilizer application, possibly to compensate for the drop in manure application. By contrast, intensity of application of planting fertilizer among the partial adopters dropped in 2007.

Adopters of improved maize varieties and inorganic fertilizers dominated the non-adopters in terms of non-crop income throughout the periods of reference. The difference in non-crop income was, however, higher between adopters of the complete package and non-adopters. Perhaps differences in education explain this variation in non-crop income. A larger proportion of the adopters, especially package adopters, had post-primary education which, possibly, provided alternative income sources. A higher male ratio in the population of the adopting households is also a possible explanation for the differences in non-crop income. This is because, in the rural setting where the farm households are located, most off-farm activities are manual, and therefore less likely to be attractive to women.

Expected maize yield is higher with adoption of farm technology than without, whether the adoption is complete or partial. But complete adoption promises higher yields than partial adoption. Yield variability is also higher among the technology adopters than the non-adopters, indicating that improved technologies are suitable for enhancing yields, but also increase production risks.

Empirical Results and Discussion

The placebo test of the equal trends assumption could not be rejected. This justified the use of DID for unbiased estimates. Table 3 outlines the DID results of maize yield differences among the different categories of adopters and non-adopters of improved maize varieties and inorganic fertilizers.

Table 2. PSM-based DID estimate of the effect of adoption of improved farm technologies on maize yield

Technology	Adoption Impact on Yield			
	Whole sample	75th Quantile	50th Quantile	25th Quantile
Complete package vs. non-adopters	229.6** (2.52)	46.290 (0.34)	162.3** (2.24)	203.3*** (3.08)
Partial adopters vs. non-adopters	23.4 (0.39)	-129.28* (-1.69)	-40.056 (-0.72)	82.5* (1.75)

t-values in parentheses

Results indicate that adoption of improved maize varieties and inorganic fertilizers by smallholders in Kenya is correlated with maize yield. The effects, however, vary by technology and across the yield quantiles. Between the complete package adopters and the non-adopters, there is a significant positive correlation between adoption and maize yield for the entire sample, and at the 25th quantile and median yield levels. The package adopters realize 203 kg and 162 kg of maize yield more than their non-adopter counterparts at the 25th and 50th quantiles, respectively. On average, the package adopters are 230 kg of maize yield better off than the non-adopters. Between the partial adopters and the non-adopters, the direction of the effect of adoption is ambiguous. At the 25th quantile of yield, the partial adopters weakly dominate the non-adopters. The reverse is true at the 75th quantile. By inference, these results indicate that package adopters are better off than partial adopters in terms of maize yield. They harvest about 120 kg of maize more at the 25th quantile and 200 kg more at the 50th quantile. On average, the package adopters harvest 253 kg of maize more than the partial adopters. This translates into over 500 kg for areas that enjoy two cropping seasons, which is a significant contribution to food security at both household and national levels.

The results in Table 3 are based on the assumption that technical efficiency (TE) of the smallholders remains unchanged. Simulated results based on TE changes are presented in Table 4. They are based on four scenarios: 100 percent TE; 75 percent rise in TE; 50 percent rise in TE; and 25 percent rise in TE over the 2004–2007 period TE scores.

Table 3. Simulated impact of technology adoption on maize yield

Technology	Adoption Impact on Yield			
	Whole sample	75th Quantile	50th Quantile	25th Quantile
100% Technical Efficiency				
Complete package vs. non-adopters	833***	1002***	855***	484***
	(3.31)	(6.98)	(10.1)	(7.21)
Partial adopters vs. non-adopters	398***	656***	245***	144**
	(2.41)	(4.68)	(3.18)	(2.12)
75% Rise in TE				
Complete package vs. non-adopters	682***	672***	853***	481***
	(3.43)	(5.95)	(10.4)	(6.95)
Partial adopters vs. non-adopters	304**	-188	145*	144**
	(2.3)	(-1.0)	(1.73)	(2.13)
50% Rise in TE				
Complete package vs. non-adopters	531***	286**	675***	491***
	(3.53)	(2.03)	(8.69)	(6.72)
Partial adopters vs. non-adopters	210**	223**	111	138**
	(2.08)	(2.18)	(1.47)	(2.1)
25% Rise in TE				
Complete package vs. non-adopters	380***	208*	441***	416***
	(3.45)	(1.71)	(6.12)	(6.02)
Partial adopters vs. non-adopters	117	47.9	61	115*
	(1.56)	(0.51)	(0.86)	(1.89)

t-values in parentheses

Assuming that the farm households were fully technically efficient, both package and partial adopters of the farm technologies under review would dominate the non-adopters in maize yield. However, the package adopters would realize more yields than the partial adopters. The highest difference would be at the median quantile, where the package adopters would harvest 610 kg of maize more than the partial adopters. On average, holding other factors constant, the package adopters experience about 435 kg of maize harvest above their partial adopter counterparts.

If the 2004–2007 TE levels of the smallholders were improved by 75 percent, the package adopters would dominate non-adopters in maize yield at all the quantiles of analysis. The partial adopters would dominate the non-adopters at the 25th and the 50th quantiles. On average, the package adopters would harvest 378 kg of maize more than the partial adopters, although the greatest yield differences between the two groups would be at the median and the 75th quantiles.

At a 50 percent rise in the 2004–2007 levels of TE, package adopters would dominate the non-adopters at all the quantiles and the partial adopters would dominate them only at the 25th and 75th quantiles. The median quantile shows the greatest yield difference between the package adopters and the partial adopters, while the 75th quantile shows the lowest yield difference, both in favour of the package adopters. Overall, the package adopters experience 321 kg more maize harvest than the partial adopters at this level of technical efficiency.

With low levels of technical efficiency, as exhibited by the 25 percent improvement over the 2004–2007 levels, partial adopters perform poorly. They are not significantly different from the non-adopters except at the 25th quantile. On the contrary, package adopters still dominate both the partial and non-adopters even at such low levels of technical efficiency. They experience 380 more kilogrammes of maize harvest than the partial adopters at the median quantile and 301 kg at the 25th quantile. At the 75th quantile, they realize 160 more kilogrammes of maize harvest. On average, the package adopters harvest 263 kg of maize more than their partial adopter contemporaries at this low level of TE.

Four important issues emerge from the above findings:

a) Inorganic fertilizers and improved maize varieties are indeed yield-increasing. The technologies, however, perform best when adopted as a package;

b) Yield returns to inorganic fertilizers and improved maize varieties are much greater when the farmers are more efficient in their farm operations;

c) Partial adoption of inorganic fertilizers and improved maize varieties could be desirable as an interim measure to increase yields only among the farm households that are already realizing very low yields; and

d) For all levels of technical efficiency, the largest maize yield increases due to adoption of inorganic fertilizers and improved maize varieties are experienced by farmers producing at the median quantile. For the non-adopter farm households producing at the 75th quantile, it may not be wise to invest in improved maize varieties and inorganic fertilizers, especially when their TE is low.

Conclusions and Policy Implications

Improved farm technologies are meant to make agriculture more rewarding, especially in terms of increased output per unit of factor input or improved quality of output. Inorganic fertilizers and improved maize varieties, in particular, are meant to increase or maintain high maize yields. In nations such as Kenya, which are heavily dependent on maize as a food staple, the underlying motivation is to enhance food security, not just among smallholders but in the entire country. It is on this premise that the Government of Kenya, in partnership with development agencies, has promoted research on and dissemination of agricultural technologies targeting maize. Improved maize varieties have been developed for different agro-ecological zones and fertilizer prices have been subsidized. Wide yield disparities, however, persist between experiment stations and the farmers' fields. This raises doubts over the yield-enhancing capacity of these critical farm technologies under the uncontrolled conditions in which smallholders operate. As a result, this study sought to analyse the effects of adoption of inorganic fertilizers and improved maize varieties on maize yields among Kenyan smallholders. The study combined PSM and DID techniques to control for both time-invariant and time-variant household heterogeneity while determining the yield differences between the adopters and non-adopters.

Results indicate that inorganic fertilizers and improved maize varieties improve yields. The magnitude of the effect of these technologies on yield, however, depends on whether a farm household adopts a complete package, and on the household's baseline yield level. Overall, households that adopt the complete package of technologies (planting fertilizer, improved maize varieties and top dressing fertilizer) dominate their partially adopting and non-adopting counterparts. The effects among adopters compared to non-adopters are greater among the households that fall within the lower end of the maize yield distribution (25th and 50th quantiles).

Partial adopters are better off than non-adopters only at the lower end of yield distribution (25th quantile). At the 75th quantile, this trend is completely reversed. With increasing efficiency, the effect of inorganic fertilizers and improved maize varieties on maize yield becomes even greater. The households producing at the median quantile realize the highest gains.

The key policy inference from these findings is that complementary agricultural technologies yield best results when they are taken up as a package rather than as individual elements. Policy makers, therefore, ought to formulate and implement policies that promote package adoption. The technology developers also have to work together and market the different complementary technology elements as a package. Furthermore, promotion of inorganic fertilizers and improved maize varieties should target areas or farm households that experience median yields because that is where the impact of adoption would be greatest. It may not make economic sense for the non-adopting farm households that are already at the upper end of the yield distribution to attempt to adopt yield-enhancing technologies. Among the households or regions experiencing below the median yield, partial adoption could be encouraged, but only as an interim intervention. Farmers have to be motivated to upgrade to package adoption.

As improved technologies are developed and promoted, we must note that adoption is necessary, but not sufficient, to enhance yields. The efficiency with which these technologies are applied in the farmers' fields is equally if not more important. Measures that promote efficient farm management ought to be identified and promoted alongside the improved farm technologies.

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