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Complementarity of inorganic fertilizers and improved maize varieties and farmer efficiency in maize production in Kenya

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Abstract

This study contributes to the literature and policy on the impact of partial and package adoption of inorganic fertilizers and improved maize varieties on yields among smallholder households in Kenya. We use a blend of the quasi-experimental difference-in-differences approach and propensity score matching to control for both time-variant and time-invariant unobservable household heterogeneity.Our findings show that inorganic fertilizers and improved maize varieties significantly improve 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, and when technical efficiency of the farmers improves. A positive effect of partial adoption is experienced only in the lower quantile of the yield distribution. The policy implication is that complementary agricultural technologies should be promoted as a package, and should target households and areas which are already experiencing low yields for greater impact.

Keywords: Technology Adoption; Yield; Difference-in-Differences; Kenya.

1. Introduction

For most sub-Sahara 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 (households that cultivate 2 hectares of land or less), 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 the most important cereal crop (McCann, 2005). This importance of maize 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 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 and widely varying across regions (Ogada *et al*., 2014a). 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 (see Makokha *et al*., 2001; Ouma *et al*., 2002; Wekesa *et al*., 2003; Olwande *et al*., 2009; and Ogada *et al*., 2010). 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 benefitting from the knowledge 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.

The present study examines the impact of adopting certified seed practices and fertilizer as a package on yield by maize farmers in Kenya. More important, we examine how farm management practices influence these impacts by simulating technical efficiency change scenarios. The objective is to determine the yield differences between adopters and non-adopters of improved maize varieties and inorganic fertilizers taking into account that the level of farmer efficiency could play an important role. Substantial gaps in knowledge exist as to the productivity impacts of the package adoption decisions. 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.

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 quantiles 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 further find that, with increased efficiency, the effect of inorganic fertilizers and improved maize varieties on maize yield becomes even larger.

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. These 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.

2. Inorganic fertilizer, improved maize varieties and productivity

It has been widely anticipated that agricultural technology development and adoption would trigger "Green Revolution" in Africa. Unfortunately, the large increases in yield and production that characterised "green revolution" in Asia are yet to be witnessed in Sub-Saharan Africa (see Adekambi *et al*., 2009). This makes it imperative to investigate why the large yield increases associated with improved seed varieties and/or inorganic fertilizer at experimental plot level have not been replicated in the farmers' fields. Consequently, a number of studies have traced the impact of improved technologies on crop yield at farm level.

In Kenya, most of the previous studies that have evaluated the impact of improved technologies on yields have relied on experimental data. For example, 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). Kenya Agricultural Research Institute has also conducted many trials at their experimental stations. Both FURP and KARI used experimental approaches but their results were significantly different. Yield levels recorded by FURP were 50% lower than those recorded by KARI. Hassan et al. (1998), thus, combined experimental data generated by FURP with survey data to evaluate the impact of inorganic fertilizer use on maize yield. They observed that optimal use of fertilizer would lead to about 30% rise in yields. In the same vein, Duflo *et al*. (2003) used controlled field experiment in western Kenya to test the yield change attributable to top-dressing fertilizer. They noted a yield rise ranging between 28% and 134% for two cropping seasons.

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.

Marenya and Barrett (2009), in an interesting study of fertilizer interventions in Western Kenya, found 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 and varying farmer efficiency levels is important for policy design and targeting. 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 from evaluating results in highly monitored field experimental plots.

3. Methodology

Here we discuss the theoretical underpinning of the study and the analytical approaches used.

3.1. Theoretical model

While a few improved maize varieties are developed to directly increase yield, most of them only increase yields indirectly by mitigating adverse effects of drought, heat, excess moisture, weeds (e.g. Striga), pests, frost, nitrogen-deficiency, diseases (e.g. ear rot, grey leaf spot, maize streak virus, northern leaf blight, smut and rust), wind, and stalk and root lodgings. Similarly, inorganic fertilizers mitigate depletion of soil nutrients. Thus, the technology package of improved maize varieties and fertilizers may be viewed from the perspective of damage control rather than direct yield enhancement. Therefore, following Ameden, Qaim, and Zilberman (2005), this study adopts damage control framework suggested by Lichtenberg and Zilberman (1986). Assuming constant-returns-to-scale agricultural production function of maize, the effective yield is viewed as a product of potential output $f_j(z,\alpha)$, and damage abatement, $g_i\ (x,N)$ (Eq. 1).

$$y_{ij} = g_i(x_{ij}, N) f_j(z_{ij}, \alpha) \tag{1}$$

Potential output is the maize output that would be realized in the absence of the damage factors. That is, if the factors being targeted by improved maize varieties and inorganic fertilizers did not exists or occur in a given maize plot. It is an increasing function of production inputs, z, and heterogeneity indicator, α, which is a function of human capital, climatic conditions and plot quality. Damage abatement is the proportion of maize harvest that would have been lost had there been no investment in damage control. It is increasing at a decreasing rate as the farmer uses alternative damage controlling inputs, x, such as pesticides and herbicides, and decreasing as prevalence of damage-causing factors, N, diminish.

Farmers face four distinct technology package options: local seed-no inorganic fertilizer ($i = 0, j = 0$) improved seed-no inorganic fertilizer ($i = 1, j = 0$) local seed-inorganic fertilizer ($i = 0, j = 1$) improved seed-inorganic fertilizer ($i = 1, j = 1$). We define the first option as no-adoption state, the second and third as partial adoption state, and the last as the full package adoption state.

From the foregoing, the farmer's problem may be defined as:

$$Max_{z,x,i,j}\pi_{ij} = pg_i(x_{ij}, N) f_j(z_{ij}, \alpha) - wz_{ij} - vx_{ij} - I_{ij} \tag{2}$$

where p, w, and v are exogenous prices for output, production inputs and alternative damage control inputs, respectively while I_{ij} is the cost of technology option ij.

The technology package option that yields the highest expected profits subject to the binding costs constraints is adopted by the farmer. Profit-maximizing inputs, conditional on technology option, are functions of prices and land quality. Thus, solving the farmer's problem recursively;

$$x_{ij}^{*} = x_{ij}^{*}(w, v, p, N) \tag{3}$$

$$z_{ij}^{*} = z_{ij}^{*}(w, v, p, N) \tag{4}$$

a) Partial or full package adoption of damage control technologies increases effective yield, holding growth conditions constant. This is true so long as damage-causing factors exist within the farmers' fields;

b) Yield gains from damage control technologies increase with the severity of the damage-causing factors and price of alternative damage control inputs. This gain is computed as the difference between yields in adoption state and yields in non-adoption state of a technology package option:

$$\Delta g = g_{1j}(x, N) - g_{0j}(x, N) \tag{5}$$

So $d\Delta g / dN > 0$ and $d\Delta g / dv > 0$.

c) Adoption of damage control technologies may increase the use of other production inputs or improve the manner in which they are managed so long as input prices remain unchanged. This increases potential output which in turn increases effective yield beyond the pure effect of damage abatement. While experimental plots are able to estimate only the pure technology effect (or "gene effect" in the case of maize variety), the yield effect which works through the potential yield function is important and must not be ignored in estimating the technology effect. Although our data do not allow us to test the impact of adoption of improved maize varieties and/or inorganic fertilizers on the use of other inputs, we hypothesize that this impact could manifest in the change in technical efficiency of the farmer. Our subsequent analysis, therefore, incorporates this additional yield effect through simulation based on technical efficiency change scenarios. This makes our estimation of impact of improved technologies on yields unique among the previous approaches. Thus, the total change in effective yield due to adoption of improved maize varieties and/or inorganic fertilizers can be decomposed as:

$$\Delta y = y_{1j} - y_{0j} = \Delta g + \Delta f_z g_{1j} \tag{6}$$

Where Δg is the yield effect arising from damage abatement due to adoption of improved maize varieties and/or inorganic fertilizers while $\Delta f_2 g_{1j}$ is the yield effect of technical efficiency change due to change in production input use occasioned by technology adoption.

d) Yield gains due to adoption of technology package option may vary with heterogeneity factors, α, and quality of plots cultivated. While some of these factors may be observable (and easy to control for), others may be unobservable (and difficult to control for). Failure to control for these factors, however, leads to biased estimates of effects of technology adoption. Thus, the essence of good evaluation is to either eliminate the bias (hardly achievable) or minimize it as much as possible.

From the above theoretical underpinning, adoption of improved maize varieties and/or inorganic fertilizers increases maize yield through damage abatement and/or increasing potential output due to increased use of other production inputs. However, isolating the contribution of these improved technologies to productivity is not trivial. 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.

3.2. Estimation Strategy

Our estimation strategy is to overcome bias arising from both observable and unobservable factors which are either time-invariant or time-variant. Consequently, we augment Difference-in-Differences (DID) as suggested by Smith and Todd (2005) with Propensity Score Matching (PSM). The novelty of using PSM is that the eventual computation of the impact of technology adoption is restricted to adopting and non-adopting households which are matched in terms of observable characteristics (Dehejia and Wahba, 2002; Smith and Todd, 2005). This helps in controlling endogeneity bias due to observable time-variant factors. DID, on the other hand, 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). Although DID cannot control for the effects of time-varying unobservable factors, it is highly likely that these factors would affect the matched households in similar ways. Thus, using PSM and DID jointly in analysing the effect of improved maize varieties and inorganic fertilizers on maize yield controls for both time-variant and time-invariant observable and unobservable factors.

To introduce the influence of management (change in use of inputs due to adoption of improved maize varieties and/or inorganic fertilizers) on the yield, we computed the technical efficiency (TE) scores of the farm households in maize production for 2004-2007 period. Data envelopment analysis (DEA) approach was used (see Coelli, 1995; Coelli *et al*., 1998 for details). Scenarios of TE changes were then developed and yield differences between complete, partial and non-adopters re-computed.

For brevity, we exclude the discussion on PSM and DEA, and concentrate on DID from which the ultimate results were derived. We treat PSM, not as an evaluation method parse, but as a tool for screening the households on which DID approach is eventually applied.

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:

$$Y_{i1} = \delta_0 + \gamma_1 X_{i1} + \varphi_i + \varepsilon_{i1} \tag{7}$$

$$Y_{i2} = (\delta_0 + \alpha) + \gamma_2 X_{i2} + \varphi_i + \varepsilon_{i2} \tag{8}$$

Subtracting (7) from (8) yields:

$$\Delta Y_i = \alpha + \gamma \Delta X_i + \Delta \varepsilon_i \tag{9}$$

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 requirement that ϕ_i be 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 9 is computed for both the adopters and the non-adopters of improved farm technologies. Consequently, DID is computed as:

$$DID = FD_A - FD_{NA} \tag{10}$$

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 approach is not able to eliminate time-varying unobserved heterogeneity. As indicated earlier, this motivated the use of PSM to restrict the analysis to adopting households suitably matched with non-adopting households on observable characteristics. The matching was done using the baseline data.

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 given (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 although, where panel data are available, DID is superior.

4. Data and descriptive statistics

The study used 2004 and 2007 waves 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 hardly used for crop production. The panel survey adopts the NASSEP IV sampling frame of the Kenya National

Bureau of Statistics (KNBS). A total of 1342 households were covered by the survey.

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

Summary statistics indicated that 25% of the farmers adopted the complete package while 27% adopted the partial package option of planting fertilizer with certified seed. Other options adopted included improved seed only (13%), planting fertilizer only (7%), planting fertilizer and top dressing fertilizer (5%), and top dressing fertilizer only (1%). This shows that non-adopters constituted 22% of the farm households. Table 1 provides these statistics.

Table 1: Summary statistics: Technologies adopted by households

Technology	Percentage of adopters
Package	25
Planting & top dressing	5
Planting fertilizer only	7
Top dressing fertilizer only	1
Certified maize seed only	13
Planting fertilizer & seed	27

Source: Authors (2019)

The statistics showed that a combination of planting fertilizer and certified maize seed was the most popular partial adoption, ranking even higher than the complete package adoption. Other categories of partial adoption had very low preference among the farm households. Thus, analysing their effects on maize yield would not yield any meaningful results. Consequently, partial adoption was taken as anything less than the full package. Output variation was, therefore, compared between:

a) Package adopters and non-adopters; and

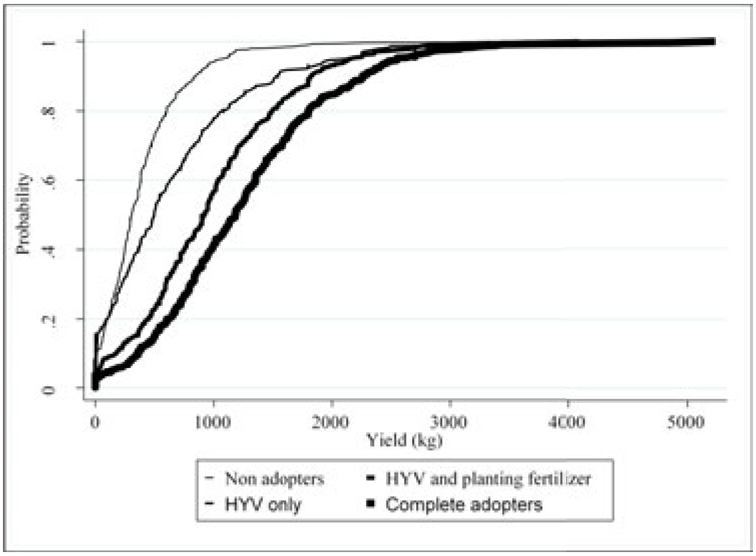
b) Partial adopters and non-adopters.

This approach also made it possible to compare the performance of the package adopters and that of the partial adopters.

The 2004 survey was used as the baseline and the 2007 survey as the follow-up. Table 2 provides a summary of technology adoption by the farm households and the covariates that are likely to affect yield. Adopters of the package experienced consistently higher yields than their non-adopter counterparts. At the baseline, partial adopters of the technologies were better in yields than the non-adopters counterparts. This was, however, reversed in 2007 when the non-adopters realised substantially higher yields. Other notable observations were: Non-adopters applied more manure than package adopters and less than the partial adopters; the ratio of household heads with post-primary education was higher for both partial and package adopters than the non-adopters; both partial and package adopters had higher non-crop income than their non-adopter counterparts; the proportion of farmers who had received agricultural credit was higher for both the partial and package adopters than the non-adopters; the adopters had higher expected yield and yield variability than the non-adopters; and the non-adopters experienced higher wage rates for farm labour than their adopter counterparts.

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



Source: Authors (2019)

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 (Kshs)	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)

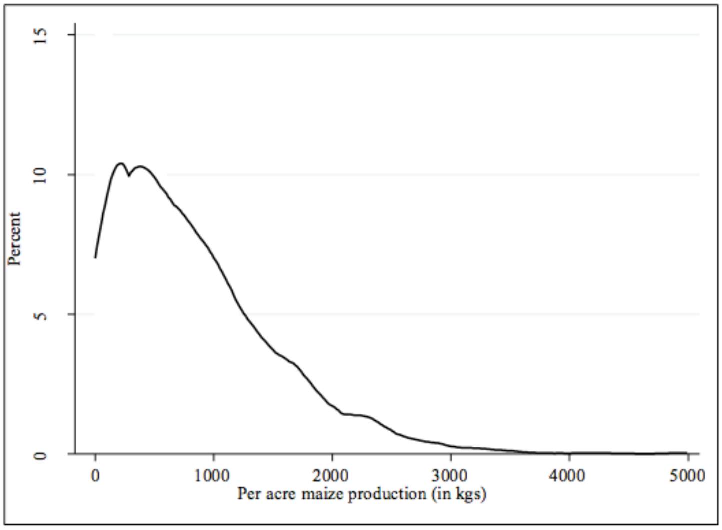
Standard deviations in parentheses

Source: Authors (2019)

Adopters of the complete package dominated partial adopters 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 provided an indication that there could be structural differences in maize yield among adopters of the complete technology package, partial adopters and non-adopters. The differences were, however, less pronounced at the lower and the upper end of the maize yield distribution.

A test of the distribution of the maize yield indicated a heavy skewness to the right (Figure 2).

Figure 2: Distribution of Maize Yield among the Households



Source: Authors (2019)

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 was higher with adoption of farm technology than without, whether the adoption was complete or partial. The expected yields were higher for complete adopters than partial adopters. Yield variability was also higher among the technology adopters than the non-adopters, indicating that improved technologies were suitable for enhancing yields although they also increased production risks.

5. Empirical results and discussion

Before implementing DID on the matched households, it was important to test the quality of matching. Thus, we conducted balancing tests and verification of the common support condition. Farm, farmer and institutional characteristics were used in the matching. Results of the balancing tests showed that most differences in the covariate means between adopters and non-adopters of improved maize varieties and inorganic fertilizers were eliminated after matching (See the t-statistics and the p-values before and after matching in Table III). In the two cases (mechanization and yield variability) where differences remained statistically significant after matching, the rates of bias reduction were 18% and 47%, respectively. This shows that matching increased the likelihood of unbiased treatment effects.

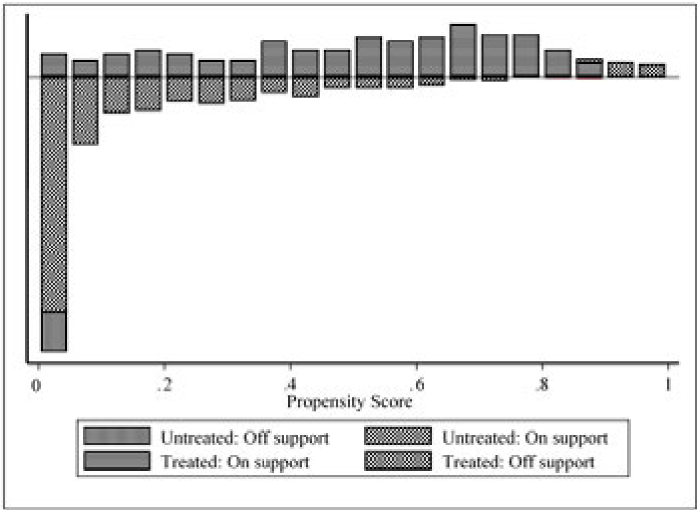
TABLE 3: DIFFERENCES IN COVARIATE MEANS BEFORE AND AFTER MATCHING

Variable	**Sample**	**Mean**			**t-test**		
		Treated	**Control**	**% bias**	**% bias reduction**	**t-stat**	**p-value**
Age	Unmatched	53.853	52.903	4.7	44.4	0.91	0.361
	Matched	53.688	53.16	2.6		0.50	0.617
Education	Unmatched	.40813	.2138	42.9	90.6	9.33	0.000
	Matched	.40502	.42338	-4.1		-0.62	0.534
Gender	Unmatched	.85336	.75	26.1	93.1	5.15	0.000
	Matched	.85125	.85841	-1.8		-0.34	0.735
Non-crop income	Unmatched	1.4e+05	1.0e+05	15.5	68.8	3.43	0.001
	Matched	1.3e+05	1.4e+05	-4.9		-0.68	0.494
Manure use	Unmatched	.27915	.4621	-38.6	68.3	-7.78	0.000
	Matched	.27957	.33751	-12.2		-2.10	0.036
Plot size	Unmatched	2.217	1.3138	26.1	98.5	7.05	0.000
	Matched	1.8581	1.8448	0.4		0.07	0.942
Wage rate	Unmatched	80.08	87.718	-24.3	68.7	-4.79	0.000
	Matched	80.17	82.563	-7.6		-1.41	0.160
Credit access	Unmatched	.28622	.25905	6.1	94.5	1.27	0.203
	Matched	.28136	.27986	0.3		0.06	0.955
Agro-ecological zone	Unmatched	.9947	.86708	52.0	92.5	8.87	0.000
	Matched	.99462	.98511	3.9		1.59	0.113
Distance to market	Unmatched	6.9969	6.391	8.3	37.0	1.73	0.084
	Matched	6.9669	6.5853	5.2		0.89	0.376
Soil type	Unmatched	.82862	.78563	10.9	80.0	2.21	0.027
	Matched	.82975	.82114	2.2		0.38	0.705
Household size	Unmatched	5.2403	4.4457	31.6	82.0	6.66	0.000
	Matched	5.2204	5.0771	5.7		0.94	0.349
Mechanized production	Unmatched	.60424	.44966	31.3	18.1	6.46	0.000
	Matched	.60036	.4738	25.6		4.27	0.000
Expected yield	Unmatched	1216.1	661.08	168.4	94.8	35.70	0.000
	Matched	1207.2	1178.6	8.7		1.33	0.184
Yield variability	Unmatched	4.9e+05	3.3e+05	28.3	47.3	6.04	0.000
	Matched	4.8e+05	5.6e+05	-14.9		-2.18	0.030

Source: Authors (2019)

Checking the overlap or region of common support was done through the visual inspection of the propensity score graph. Results indicated that some treated and untreated households were indeed off-support (see Figure 3). That is, they had no matches. Including such households in the impact evaluation would lead to unreliable estimate of impact attributable to adoption of inorganic fertilizers and certified seeds. This justified the use of PSM in the study because it ensured that comparison was restricted to the matched households. That is, all the households off-support were left out of the impact evaluation.

Figure 3: Propensity Score Distribution and Common Support for Propensity Score Estimation



Source: Authors (2019)

The average technical efficiency (TE) of the same farm households was 61% (See Ogada *et al*., 2014b). This implied that the maize yield among the smallholders could still be produced even if the inputs were reduced by 39%. Table 4 outlines the DID results of maize yield differences among the different categories of adopters and non-adopters of improved maize varieties and inorganic fertilizers based on the 61% TE levels.

Table 4: 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)

Source: Authors (2019)

*, **, *** mean significant at 10%, 5% and 1%, respectively; t-values in parentheses

Results showed that adoption of improved maize varieties and inorganic fertilizers by smallholders in Kenya was correlated with maize yield. The effects, however, varied by technology and across the yield quantiles. Between the complete package adopters and the non-adopters, there was 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 realized 203 kg and 162 kg of maize yield more than their non-adopter counterparts at the 25th and the 50th quantiles, respectively. On average, the package adopters were 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 was ambiguous. At the 25th quantile of yield, the partial adopters weakly dominate the non-adopters. The reverse was true at the 75th quantile. By inference, these results indicated that package adopters were better off than partial adopters in terms of maize yield. They harvested about 120 kg of maize more at the 25th quantile and 200 kg more at the 50th quantile. On average, the package adopters harvested 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.

To understand the role of change of TE of the smallholders in yield levels, we take four hypothetical scenarios: 100 percent TE; 75 percent rise in TE; 50 percent rise in TE; and 25 percent rise in TE. Assuming other factors remain the same, we estimate what the maize yield would be at the assumed levels of TE and re-estimate the impact of adoption of inorganic fertilizers and certified seed using the PSM-DID approach as earlier explained. The results are presented in Table 5.

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 would experience about 435 kg of maize harvest above their partial adopter counterparts.

Table 5: 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)

Source: Authors (2019)

*, **, *** mean significant at 10%, 5% and 1%, respectively; t-values in parentheses

If the 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 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 had the greatest yield difference between the package adopters and the partial adopters, while the 75th quantile had the lowest yield difference, both in favour of the package adopters. Overall, the package adopters would 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, partial adopters would perform poorly. They would not be significantly different from the non-adopters except at the 25th quantile. On the contrary, package adopters would still dominate both the partial and non-adopters even at such low levels of technical efficiency. They would realize 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 would realize 160 more kilogrammes of maize harvest. On average, the package adopters would 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:

1. Inorganic fertilizers and improved maize varieties are indeed yield-increasing. The technologies, however, perform best when adopted as a package;
2. Adoption of inorganic fertilizers and improved maize varieties is likely to increase farmer efficiency. If this occurs, yield returns would be much greater;
3. 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
4. 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.

5. Conclusion 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 showed that inorganic fertilizers and improved maize varieties improved yields. The magnitude of the effect of these technologies on yield, however, depended on whether a farm household adopted a complete package, and on the household's baseline yield level. Overall, households that adopted the complete package of technologies (planting fertilizer, improved maize varieties and top dressing fertilizer) dominated their partially adopting and non-adopting counterparts. The effects among adopters compared to non-adopters were greater among the households within the lower end of the maize yield distribution (25^{th} and 50^{th} quantiles).

Partial adopters were better off than non-adopters only at the lower end of yield distribution (25^{th} quantile). At the 75^{th} quantile, this trend completely reversed. With increasing efficiency, the effect of inorganic fertilizers and improved maize varieties on maize yield was even greater. The households producing at the median quantile realized 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 complete 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.

Biographical Notes

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References

Abadie, A. (2005) 'Semi-parametric Difference in Difference Estimators', *Review of Economic Studies*, 72: 1–19.

Alene, A., and Manyong, V.M. (2007) 'The Effect of Education on Agricultural Productivity under Traditional and Improved Technology in Northern Nigeria: An Endogenous Switching Regression Analysis', *Empirical Economics*, 32: 141–159.

Ameden, H., Qaim, M., and Zilberman, D. (2005) Adoption of Biotechnology in Developing Countries in Joseph Cooper, Leslie Marie Lipper, and David Zilberman (eds.) Agricultural Biodiversity and Biotechnology in Economic Development, 329-57. New York: Springer Science+Business Media.

Barrett, C.B., Moser, C.M., McHugh, O.V., and Barison, J. (2004) 'Better Technology, Better Plots, or Better Farmers? Identifying Changes in Productivity and Risk among Malagasy Rice Farmers', *American Journal of Agricultural Economics*, 86(4): 869-888.

Coelli, T. J. (1995) 'Recent developments in frontier modeling and efficiency measurement', *Australian Journal of Agricultural Economics*, 39(3): 219–45.

Coelli, T., Rao, D., and Battese, G. (1998) An Introduction to Efficiency and Productivity Analysis, Sixth Printing (2002). Massachusetts: Kluwer Academic Publishers.

Crost, B., Shankar, B., Bennett, R., and Morse, S. (2007) 'Bias from Farmer Self-selection in Genetically Modified Crop Productivity Estimates: Evidence from Indian Data', *Journal of Agricultural Economics*, 58(1): 24–36.

De Groote, H., Owuor, G., Doss, C., Ouma, J., Muhammad, L., and Danda, K. (2005) 'The Maize Green Revolution in Kenya Revisited', *E-Jounal of Agricultural and Development Economics*, 2(1): 32–49.

Dehijia, R.H., and Wahba, S. (2002) 'Propensity Score Matching Methods for Nonexperimental Causal Studies', *The Review of Economics and Statistics*, 84(1): 151-161.

Dorfman, J.H. (1996) 'Modeling Multiple Adoption Decisions in a Joint Framework', *American Journal of Agricultural Economics*, 78: 547-557.

Duflo, E., Kremer, M., and Robinson, J. (2003) Understanding Technology Adoption: Fertilizer in Western Kenya, Preliminary Results from Field Experiments, Working Paper, MIT, Harvard University and Princeton University.

Duflo, E., Kremer, M., and Robinson, J. (2008) 'How High are Rates of Return to Fertilizer: Theory and Experimental Evidence from Kenya', *American Economic Review*, 98: 482-488.

Foster, A., and Rosenzweig, M. (1995) 'Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture', *Journal of Political Economy*, 103(6): 1176–1209.

Hassan, R., Murithi, F., and Kamau, G. (1998) 'Determinants of Fertilizer Use and the Gap between Farmers. Maize Yields and Potential Yields in Kenya' in Rashid Hassan (ed.) Maize Technology Development and Transfer: A GIS Application for Research Planning in Kenya. Wallingford, UK: CAB International.

Jalan, J., and Ravallion, M. (2003) 'Does Piped Water Reduce Diarrhea for Children in Rural India?', *Journal of Econometrics*, 112: 153–173.

Karanja, D. (1996) An Economic and Institutional Analysis of Maize Research in Kenya, MSU International Development Working Paper 57, Department of Agricultural Economics, Michigan State University, East Lansing.

Koenker, R., and Hallock, K. (2001) 'Quantile Regression', *Journal of Economic Perspectives*, 15: 143–156.

Lichtenberg, E., and Zilberman, D. (1986) 'The Econometrics of Damage Control: Why Specification Matters', *The American Journal of Agricultural Economics*, 68(2): 261-73.

Maddala, G.S. (1983) Limited-Dependent and Qualitative Variables in Econometrics. New York: Cambridge University Press.

Makokha S, Kimani S, Mwangi W, Verkuijl H, Musembi F. (2001) 'Determinants of Fertilizer and Manure Use for Maize Production in Kiambu District, Kenya'. CIMMYT (International Maize and Wheat Improvement Center), Mexico, D.F.

Marenya, P.P., and Barrett, C.B. (2009) 'State-Conditional Fertilizer Yield Response on Western Kenyan Farms', *American Journal of Agricultural Economics*, 91(4): 991-1006.

McCann, J.C. (2005) 'Maize and Grace: Africa's Encounter with a New World Crop, 1500–2000'. Cambridge: Harvard University Press.

Mendola, M. (2007) 'Farm Household Production Theories: A Review of 'Institutional' and 'Behavioral' Responses', Asian Development Review, 24(1): 49–68.

Ogada, M.J., Nyangena, W., and Yesuf, M. (2010) 'Production risk and farm technology adoption in rain-fed semi-arid lands of Kenya'. AfJARE 4(2).

Ogada, M.J., Mwabu, G., and Muchai, D. (2014a) 'Farm technology adoption in Kenya: a simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions'. *Agricultural and Food Economics,* 2:12.

Ogada, M.J., Muchai, D., Mwabu, G., and Mathenge, M. (2014b) 'Technical Efficiency of Kenya's Smallholder Food Crop Farmers: Do Environmental Factors Matter?' *Environment, Development and Sustainability* 16 (5):1065-1076

Olsen, R.J. (1980) 'A Least Squares Correction for Selectivity Bias', *Econometrica*, 48(7): 1815–1820.

Olwande, J., Sikei, G., Mathenge, M. (2009) 'Agricultural Technology Adoption: A Panel Analysis of Smallholder Farmers' Fertilizer use in Kenya'. CEGA Working Paper Series No. AfD-0908. Centre of Evaluation for Global Action. University of California, Berkeley.

Ouma, J., Murithi, F., Mwangi, W., Verkuijl, H., Gethi, M., and De Groote, H. (2002) 'Adoption of Maize Seed and Fertilizer Technologies in Embu District, Kenya'. CIMMYT (International Maize and Wheat Improvement Center), Mexico, D.F.

Rosegrant, M.W., Ringler, C., Msangi, S., Zhu, T., Sulser, T., Valmonte-Santos, R., and Wood, S. (2007) 'Agriculture and Food Security in Asia: The Role of Agricultural Resources Knowledge in a Changing Environment', *Journal of Semi-Arid Tropical Agricultural Resources*, 4: 1-35.

Rosegrant, M.W., Ringler, C., Sulser, T., Ewing, M., Palazzo, A., Zhu, T., Nelson, G.C., Koo, J., Robertson, R., Msangi, S., and Batka, M. (2009) Agriculture and Food Security under Global Change: Prospects for 2025/2050. Background note for supporting the development of CGIAR strategy and Results Framework. Washington, D.C.: International Food Policy Research Institute.

Smith, J.A., and Todd, P.E. (2005) 'Does Matching Overcome LaLonde's Critique of Experimental Estimators?' *Journal of Econometrics*, 125: 305–353.

Suri, T. (2011) 'Selection and Comparative Advantage in Technology Adoption', *Econometrica*, 79(1): 159–209.

Wekesa, E., Mwangi, W., Verkuijl, H., Danda, V.K., and De Groote, H. (2003) 'Adoption of Maize Technologies in the Coastal Lowlands of Kenya'. CIMMYT, Mexico, D.F.