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IMPACT OF FERTILIZER ON MAIZE YIELD GROWTH: DISPARITY AMONG AGRO-ECOLOGICAL ZONES OF ETHIOPIA

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Abstract

This study examined the disparity in impact of adoption of fertilizer of any kind (organic, inorganic or both) on maize yield growth using 1040 sample farm households in four major maize growing agro-ecological zones of Ethiopia. Propensity score matching technique was employed since it is an increasingly utilized standard approach for evaluating impacts using observational data. It was found that adoption of fertilizer of any kind (organic, inorganic or both) didn't have the desired positive and significant impact on maize yield growth in all of the agro-ecological zones considered. Therefore, this study recommended that the agricultural research and extension system of the country should be strengthened to further take into account the differences among different agro-ecological zones and areas having high variability in landscape positions, rain fall, soil characteristics and farming systems in order to generate and scale-up appropriate improved agricultural technologies and information that suits to the specific conditions of each maize producing land pockets of the country.

INTRODUCTION

Roughly 80 percent of Africa's poor live in rural areas, and even those who do not will depend heavily on increasing agricultural productivity to lift them out of poverty (Haggblade, 2004). Accordingly, seventy percent of all Africans— and nearly 90 percent of the poor—work primarily in agriculture. As consumers, all of Africa's poor—both urban and rural—count heavily on the efficiency of the continent's farmers. Farm productivity and production costs largely determine the prices of basic food stuffs, which account for 60–70 percent of total consumption expenditures by low-income groups (Haggblade, 2004). The Sub-Saharan Africa agriculture involves diverse crops and livestock but productivity is particularly important for cereals and starchy roots, which provide two-thirds of the total energy intake for the population (three-quarters for the poor) (AGRA, 2013 citing Diao, Thurlow, Benin, & Fan, 2012). According to the Africa Human Development Report 2012 (United Nations Development Programme [UNDP], 2012), more than 75% of cereals and almost all root crops come from domestic agriculture and not imports (AGRA, 2013).

Many of the rural poor worldwide are smallholder farmers, and in most of South and South East Asia, and in much of sub-Saharan Africa, agriculture is dominated by smallholders (Jama and Pizarro, 2008 citing Birthal et al. 2005 and Kydd et al. 2002). In strategic terms, smallholder farming is generally viewed as indispensable to development as a whole (Jama and Pizarro, 2008). One common answer for the question why smallholders remain poor is that despite being relatively efficient users of resources, they remain poor because most poor countries provide them with only limited technical and economic opportunities to which they can respond and this is particularly the case in Africa, the only region in the world where per capita agricultural productivity has remained stagnant over the past 40 years (Jama and Pizarro, 2008 citing Sanchez et al. 2005).

Until recently agricultural growth had resulted from an expansion of the area under crops or grazing rather than higher yields. However, demographic pressures have largely exhausted available land and in many areas, average farm sizes are falling, with typically areas of 2–5 ha dominating (Adekunle et al., 2012). At the same time, land quality has fallen. Data on nutrient balances over the past 30 years suggest that African soils have sustained annual net losses of nitrogen, phosphorus, and potassium on the order of 22, 2.5, and 15 kilograms per hectare respectively and this soil mining may contribute from one-third to as much as 80 percent of farm output in some locations (Haggblade, 2004). The lack of sufficient infrastructure, including rural access roads, irrigation, and land management capabilities, has resulted in the small amount of land available not being used at full potential. This problem is amplified by the common lack of capital and available funds to finance additional capital acquisition and insufficient financing continues to manifest in several ways, often equating to lack of dependable farm inputs such as high-yielding varieties of seeds, appropriate fertilizers, or cheap credit (AGRA, 2013 citing FAO, 2009).

Fortunately, African and donor governments have come to realize that they have marginalized agriculture for too long (Haggblade, 2004). Accordingly, through the consultative process of the New Partnership for Africa's Development (NEPAD), the African heads of state have identified agriculture as a priority sector for stimulating economic growth and poverty reduction in Africa. Domestically, NEPAD aims to facilitate policies, strategies, and partnerships that will enhance the performance of agriculture in Africa. Internationally, it will continue to lobby for a more level playing field for African smallholders in international markets while promoting sub-regional cooperation and market development. Only sustained high-level political support will result in the policy incentives and long-term financial support to agricultural institutions that will, together, prove necessary for accelerating Africa's agricultural growth (Haggblade, 2004).

Some exciting efforts of African farmers and researchers in the past decade or so have significantly raised agricultural productivity in certain countries and for certain products (Haggblade, 2004). Notably, Ethiopia has more than doubled its domestic grain production (from 8 million metric tons in 2000 to 15.6 million metric tons in 2010) and is now Sub-Saharan Africa's second largest grain producer behind Nigeria (AGRA, 2013 citing USDA, 2012). Today, after widespread adoption by both commercial farmers and small holders, farmers now plant 58 percent of all maize area in East and Southern Africa to new high-yielding varieties, which on average out yield traditional varieties by 40–50 percent even without fertilizer (Haggblade, 2004). Despite the obvious challenges facing Sub-Saharan African countries with respect to agricultural productivity, recent successes recorded in Kenya, Malawi, Zambia, Uganda, Tanzania, Ethiopia, Mali, Burkina Faso, among other countries, have shown it is possible to achieve sustained agricultural growth in Sub-Saharan Africa (AGRA, 2013)

Given that Africa must grow faster than the rest of the world just to keep up with its increasing population, it remains true that the many individual successes achieved over the past half century have simply not been sufficient in number or scale (Haggblade, 2004). Due to the wide variety of local contexts in the African continent, a pluriform approach that specifically addresses the diversity is likely to work more effectively in increasing agricultural performance (Bindraban et al., 2009). Yield gap for most crops could be reduced by appropriate use of improved crop varieties; recommended application levels of appropriate fertilizers; and adequate management of nutrients, water, pests, and diseases (AGRA, 2013). Even if, in rare circumstances, smallholder farmers access irrigation, financing, technology, and adequate inputs, the lack of market access often lead to production failures. Market access problems persist in many areas, often resulting in many farmers not being able to sell their produce and hence resorting to subsistence production for their livelihoods (AGRA, 2013).

Though inadequate in scale and scope to outrun Africa's daunting demographics, these successes offer potentially important lessons for replicating and scaling up successful efforts more frequently in the future (Haggblade, 2004). Accordingly, drawing lessons from past success requires identifying a range of successful and less successful episodes and then studying and comparing them. With a wider range of institutional options now available, more evaluation is needed of what works well in what contexts (World Bank, 2007). In response to this need, the objective of this study is to identify the difference in the impact of use of fertilizer of any kind (organic, inorganic or both) on maize yield growth among major maize growing agro-ecological zones of Ethiopia.

MATERIALS AND METHODS
Analytical Framework for Evaluation

Assessing the impact of any intervention requires making an inference about the outcomes that would have been observed for program participants had they not participated (Smith and Todd, 2001). The evaluation problem can be regarded as a missing-data problem since, at a moment in time, each person is either in the program under consideration or not, but not both (Blundell and Dias, 2000). Accordingly, constructing the counterfactual is the central issue that evaluation methods address.

Assuming a lack of un-observables in which treatment assignment is said to be independent of potential outcomes conditional on the set of covariates X, one approach called the matching method aims to select sufficient observable factors that any two individuals with the same values of these factors will display no systematic differences in their reactions to the policy reform (Blundell and Dias, 2000; Millimet and Tchernis, 2009). Consequently, if each individual undergoing the reform can be matched with an individual with the same matching variables who has not undergone the reform, the impact of the reform on individuals of that type can be measured (Blundell and Dias, 2000). To solve the dimensionality problem that is likely to arise if X is a lengthy vector, Rosenbaum and Rubin (1983) propose using the propensity score, $P(X_i) = \Pr(T_i = 1|X_i)$, instead of X as the conditioning variable (Millimet and Tchernis, 2009).

The most prominent evaluation parameter is the so-called *average treatment effect on the treated (ATT)* given by

$$\tau_{ATT} = E(\tau|D=1)= E[Y(1)|D=1]-E[Y(0)|D=1],$$

which focuses explicitly on the effects on those for whom the intervention is actually intended (Caliendo and Kopeinig, 2008). Accordingly, the expected value of ATT is defined as the difference between expected outcome values with and without treatment for those who actually participated in treatment.

Such matching estimator as PSM will not, however, necessarily work in all circumstances (Caliendo and Kopeinig, 2008; Heinrich et al., 2010). Accordingly, some identifying assumptions have to be met to produce valid impact estimates:

Assumption 1 (Conditional Independence Assumption or CIA): there is a set X of covariates, observable to the researcher, such that after controlling for these covariates, the potential outcomes are independent of the treatment status:

$$(Y_1, Y_0) \perp D \mid X$$

This property is also known as *un-confoundedness or selection on observables*.

Assumption 2 (Common Support Condition): for each value of X, there is a positive probability of being both treated and untreated:

$$0< P(D = 1| X) < 1$$

The second requirement is also known as overlap condition, because it ensures that there is sufficient overlap in the characteristics of the treated and untreated units to find adequate matches (or a *common support*). When these two assumptions are satisfied, the treatment assignment is said to be *strongly ignorable* (Rosenbaum & Rubin, 1983).

In fact, when the parameter of interest is the ATT, the CIA assumption can be relaxed to: $Y_0 \perp D|X$ since we need only to construct the counterfactual for the treated individuals.

Given that CIA holds and assuming additionally that there is overlap between both groups, the PSM estimator for ATT can be written in general as

$$\tau^{PSM}_{ATT} = E_{P(X)|D=1}\{E[Y(1)|D=1, P(X)]-E[Y(0)|D=0, P(X)]\}$$

To put it in words, the PSM estimator is simply the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants (Caliendo and Kopeinig, 2008).

In PSM, the procedure for estimating the impact of an intervention can be divided into three straightforward steps: (1) Estimate the propensity score, (2) Choose a matching algorithm that will use the estimated propensity scores to match untreated units to treated units as well as (3) Estimate the impact of the intervention with the matched sample and calculate standard errors (Heinrich et al., 2010).

Once the propensity scores have been estimated, the propensity scores of the treatment group can be matched to propensity scores of subjects in a comparison group and this allows one to estimate the ATT.

The most common implementation of propensity score matching is one-to-one or pair matching, in which pairs of treated and untreated subjects are formed, such that matched subjects have similar values of the propensity score. However, other approaches can also be used (Austin, 2011).
The true propensity score is a balancing score. Therefore, in strata of subjects that have the same propensity score, the distribution of measured baseline covariates will be the same between treated and untreated subjects. Appropriate methods for assessing whether the propensity score model has been adequately specified involve examining whether the distribution of measured baseline covariates is similar between treated and untreated subjects with the same estimated propensity score (Austin, 2011). One approach uses a two-sample t-test to check if there are significant differences in covariate means for both groups (Caliendo and Kopeinig, 2008 citing Rosenbaum and Rubin, 1985). Before matching differences are expected, but after matching the covariates should be balanced in both groups and hence no significant differences should be found (Caliendo and Kopeinig, 2008). If, after conditioning on the propensity score, there remain systematic differences in baseline covariates between treated and untreated subjects, this can be an indication that the propensity score model has not been correctly specified (Austin, 2011).

Data and Variables

The data utilized for this study is acquired from the third wave of the Ethiopia Socioeconomic Survey (ESS) 2015-2016. The ESS is a collaborative long-term project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) team to collect panel data. The ESS collects information on household agricultural activities along with other information on the households like human capital, other economic activities, access to services and resources. ESS uses a nationally representative sample of over 5,000 households living in rural and urban areas. The urban areas include both small and large towns. The sample is a two-stage probability sample. The first stage of sampling entailed selecting primary sampling units, which are a sample of the CSA enumeration areas (EAs). The second stage of sampling was the selection of households to be interviewed in each EA. A total of 433 EAs were selected based on probability proportional to size of the total EAs in each region out of which 290 were rural, 43 were small town EAs from ESS1, and 100 were EAs from major urban areas. In order to ensure sufficient sample size in the most populous regions (Amhara, Oromiya, South Nations, Nationalities and People, and Tigray) and Addis Ababa, quotas were set for the number of EAs in each region. The sample is not representative for each of the small regions including Afar, Benishangul-Gumuz, Dire Dawa, Gambella, Harari, and Somali regions. However, estimates can be produced for a combination of all smaller regions as one “other region” category. During wave 3, 1255 households were re-interviewed yielding a response rate of 85 percent. Attrition in urban areas is 15% due to consent refusal and inability to trace the whereabouts of sample households.
LnYield stands for the natural logarithmic transformation of the yield of maize per unit of land cropped measured in quintals per hectare.

RESULTS AND DISCUSSIONS

Propensity Scores Estimation using Probit Model

The descriptive statistics showed a tentative impact of fertilizer adoption on increasing yield in some of the agro-ecological zones. Nevertheless, a mere comparison of yield has no causal meaning since fertilizer adoption is endogenous. And it is difficult to attribute the change to adoption of fertilizer since the difference in yield might be owing to other determinants. To this end, a rigorous impact evaluation method; namely, Propensity Score Matching has to be employed to control for observed characteristics and determine the actual attributable impact of fertilizer adoption on yield growth in different maize producing agro-ecological zones of Ethiopia. Propensity scores for adopters and non-adopters were estimated using a probit model to compare the treatment group with the control group. In this regard, only those significant variables were used in estimating the propensity scores for each agro-ecological zone. The check for ‘overlap condition’ across the treatment and control groups was done and the result as indicated on figure 1 showed that the overlap condition is satisfied for all the four agro-ecological zones considered as there is substantial overlap in the distribution of the propensity scores of both adopters and non-adopters.

For tropic-cool/semiarid zone, the propensity score for adopters ranged between 0.0550972 and 0.9880359 while it ranged between 1.44e-10 and 0.9489585 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranged between 0.05509721 and 0.9880359. For tropic-cool/sub-humid zone, the propensity score for adopters ranged between 0.1414042 and 0.9141887 while it ranged between 0.1191701 and 0.8545939 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranged between 0.14140416 and 0.91418874. For tropic-cool/humid zone, the propensity score for adopters ranged between 0.1706593 and 0.8400287 while it ranged between 0.0868637 and 0.7509327 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranged between 0.17065927 and 0.84002866. For tropic-warm/ semiarid zone, the propensity score for adopters ranged between 0.3294889 and 0.9806739 while it ranged between 0.252204 and 0.9238907 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranged between 0.32948886 and 0.98067387. When matching techniques are employed, observations whose propensity score lies outside this range were discarded.

Assessing Matching Quality

Checking whether the matching procedure is able to balance the distribution of the relevant variables in both the control and treatment group is important in using the propensity score method. The before and after matching covariate balancing tests presented on table 1 suggested that the proposed specification of the propensity score is fairly successful in balancing the distribution of covariates between the two groups as indicated by decreasing pseudo R^2 and mean standardized bias for all zones, the insignificant p-values of the likelihood ratio test for tropic-cool/semiarid zone and satisfied interval value of Rubin's R (ratio of treated to (matched) non-treated variances of the propensity score index) after matching for all zones except tropic-warm/semiarid.

Table 1: Propensity Score Matching Quality Test

Agro-Ecological Zone	Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias	R	%Var
Tropic-cool/semiarid	Unmatched	0.245	136.75	0.000	35.6	24.3	0.43*	56
	Matched	0.079	39.29	0.000	15.1	12.9	1.14	22
Tropic-cool/sub-humid	Unmatched	0.105	50.84	0.000	26.9	28.5	1.22	14
	Matched	0.024	11.82	0.461	6.6	3.8	1.46	14
Tropic-cool/humid	Unmatched	0.076	17.83	0.003	34.4	30.5	1.40	0
	Matched	0.001	0.24	0.999	2.1	1.3	0.93	0
Tropic-warm/semiarid	Unmatched	0.221	9.94	0.127	69.8	59.7	1.02	50
	Matched	0.036	1.96	0.742	10.1	0.0	3.26*	50

* if B>25%, R outside [0.5; 2]

Average Treatment Effects Estimation

Different matching algorithms are available for Propensity Score Matching with nearest neighbor matching and kernel matching being the most common ones (Kikulwe et al., 2012 citing Caliendo and Kopeinig, 2008). Accordingly, nearest neighbor matching matches adopters with non-adopters with the nearest propensity score, while controlling for differences between adopters and non-adopters whereas kernel matching computes treatment effects by deducting from each outcome observation in the treatment group a weighted average of outcomes in the control group. Table 3 depicted the average impact of fertilizer adoption on maize yield growth using nearest neighbor matching one and five (NN=1 and

NN=5) as well as Epanechnikov kernel matching with two band widths (BW=0.03 and BW=0.06). Accordingly, all or most of the matching algorithms employed supported the hypothesis that fertilizer adoption has a positive and significant impact on yield growth in only two of the four agro-ecological zones considered, namely tropic-cool/humid and tropic-cool/sub-humid. Moreover, fertilizer adoption had a higher impact on yield growth in tropic-cool/humid zone, ranging from 43-51%, compared to that in tropic-cool/sub-humid zone, ranging from 28-40%.

Table 2: Average Treatment Effects Estimation using Different Propensity Score Matching Estimators

Agro-ecological Zone	Outcome Variable	Matching Algorithm	ATT (Std. Err.)
Tropic-cool/semiarid	LnYield	Nearest Neighbor (NN=1)	-0.021(0.221)
		Nearest Neighbor (NN=5)	0.017(0.195)
		Kernel (BW=0.03)	-0.018(0.173)
		Kernel (BW=0.06)	-0.027(0.179)
Tropic-cool/sub-humid	LnYield	Nearest Neighbor (NN=1)	0.282*(0.197)
		Nearest Neighbor (NN=5)	0.399***(0.163)
		Kernel (BW=0.03)	0.321***(0.134)
		Kernel (BW=0.06)	0.304***(0.112)
Tropic-cool/humid	LnYield	Nearest Neighbor (NN=1)	0.506**(0.227)
		Nearest Neighbor (NN=5)	0.434**(0.184)
		Kernel (BW=0.03)	0.501***(0.181)
		Kernel (BW=0.06)	0.474***(0.157)
Tropic-warm/semiarid	LnYield	Nearest Neighbor (NN=1)	0.365(0.542)
		Nearest Neighbor (NN=5)	-0.451(0.385)
		Kernel (BW=0.03)	-0.082(0.519)
		Kernel (BW=0.06)	0.318(0.686)

***, **, * indicate significance at 1%, 5% & 10% level respectively and bootstrapped standard errors are based on 100 replications.
Source: Own computation, 2020

CONCLUSION AND RECOMMENDATIONS

This study, which is undertaken to identify the disparity in the impact of adoption of fertilizer on maize yield growth among different major maize producing agro-ecologic zones of Ethiopia, finally concludes that adoption of fertilizer didn't have the desired positive and significant impact on yield growth in all of the different major maize producing agro-ecologic zones of the country. Moreover, its impact greatly varied among the zones. Therefore, this study recommended that the agricultural research and extension system of the country should be strengthened to further take into account the differences among different agro-ecological zones and areas (like zones, woredas and “kebeles”/villages) having high variability in landscape positions, rain fall, soil characteristics and farming systems in order to generate and scale-up appropriate improved agricultural technologies and information that suits to the specific conditions of each maize producing land pockets of the country.

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