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Impact of DroughtTEGO® hybrid maize variety on agricultural productivity and poverty alleviation in Kenya

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Impact of DroughtTEGO® maize hybrids on agricultural productivity and poverty reduction among small-scale maize farmers were analyzed using 642 households in Kenya. The Water Efficient Maize for Africa (WEMA) project coordinated by the African Agricultural Technology Foundation (AATF) developed the varieties. While on-farm production output and farmers' testimonies indicate significantly high productivity over other varieties, a rigorous assessment of impacts at household level is missing. Direct comparison of maize income, total household income and poverty indices shows significant differences between adopters and non-adopters. However, since the observed estimates can be due to differences in both observable and non-observable characteristics between adopters and non-adopters, we cannot have any causal interpretation. This study, therefore, utilized the counterfactual outcome framework based on propensity score methods (PSM) to control for such differences. The results of PSM showed that adoption of DroughtTEGO® maize varieties led to significant increase in maize income by 82%, total income by 75%, and reduced the depth of poverty by 46-point margins. The study recommends formulation and implementation of appropriate policies to improve the adoption of DroughtTEGO® hybrid maize varieties across the country.

Key words: DroughtTEGO® hybrid, poverty reduction, impact assessment, maize, Kenya.

INTRODUCTION

Maize (*Zea mays* L.) is considered an essential food crop and is grown by small-scale farmers for both home

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consumption and local markets in Kenya. The main maize producing basket includes Bungoma, Trans Nzoia, Nakuru, Narok and Uasin Gishu counties. Other areas that grow maize include Kakamega, Vihiga, Busia, Siaya, Homa Bay, Migori, Kisumu, Nyeri, Meru, Embu, Machakos, Kitui, Tana River, Murang'a, Bomet and Isiolo counties. The consumption curve of maize in Kenya is moving upwards, as there was about 2.3 times increase in maize consumption by 2016 over 2005 (FAO, 2016). The growing trend in maize consumption is partly explained by rapid population growth estimated at 2.6% per annum, an indication that the country needs to take robust measures to increase maize productivity. However, such measures cannot be taken unless farmers use high yielding and stress tolerant varieties that have positive impact on productivity. There are many maize hybrid varieties grown in Kenya – the Kenya Plant Health Inspectorate Service (KEPHIS) lists about 338 maize varieties grown in Kenya by 2017 (Kephis, 2017).

The Water Efficient Maize for Africa (WEMA) project in partnership with CIMMYT, Monsanto and five National Agricultural Research Systems for Kenya, Uganda, Tanzania, Mozambique and South Africa, developed drought tolerant maize hybrids that were tested and released in Kenya.

The overall goal of the project was to enhance maize productivity by protecting against drought effects for improved livelihoods of particularly resource-limited smallholder farmers. A total of 60 hybrids were released in Kenya for commercialization. The hybrids were branded and commercialized as DroughtTEGO® maize hybrid varieties. Examples of these hybrids include WE1101, WE2101, WE2104, WE2109, WE3101, WE3102, WE3104, WE3105 and WE3106 (Oikeh et al., 2014; Edge et al., 2018). On-farm production output and farmers' testimonies showed significant yield advantages with an average yield of about 4.5 t/ha within three years of commercialization of the varieties when compared with local varieties that yield about 2.8 t/ha (Situma, 2018). An assessment of impacts of adoption of the hybrids at household level has not been established. Thus, this study aims to understand the extent to which DroughtTEGO® adoption contributes to maize productivity and poverty reduction.

Generally, the decision to adopt any agricultural technology is a function of the net benefits that the farmer expects to gain; and studying how small-scale farmers can improve their livelihoods is a central issue of economic development in developing countries like Kenya. Adoption of agricultural technologies can reduce poverty through direct and indirect effects. The renowned direct effects of technology adoption include productivity gains and per unit cost reductions. These two translate into increase in incomes that subsequently lead to poverty reduction. Indirectly the technologies can reduce poverty through reduced food prices and growth of related non-farm sectors that benefit through availability of raw materials.

Some studies in countries in Asia and Latin America have estimated that the use of improved seeds can increase yields and farmers' income (de Janvry and Sadoulet, 2001; Evenson and Gollin, 2003; Doss, 2006; Matuschke and Qaim, 2009). However, these kinds of studies are relatively few in Africa (Kassie et al., 2011). However, some studies have shown contradicting information on the effects of technology adoption. For example, Hossain et al. (2006) found that adoption of rice varieties that are high yielding has a positive effect on the richer households, but a negative effect on the poor households. Others observed that the adoption of high yielding maize varieties increased the crop incomes of adopters moderately (Bourdillon et al., 2002). Howard et al. (2003) also, found non-significant difference in income between farmers using improved maize seeds and traditional seeds after payment of the input loans acquired through Sasakawa-Global project in Mozambique. The disagreement of these findings clearly justifies the need for further research on this topic in Africa.

The generated information will guide governments on policy on adoption of technologies and donor community on supporting promotion and dissemination of such technologies. The present study, therefore, is the first attempt to quantify the benefits of adoption of DroughtTEGO® on maize income, household income and livelihoods improvement.

METHODOLOGY

Surveys and data

The data for this analysis came from 642 maize farmers in Kenya. A multi-stage, clustered, randomized sampling procedure was used. Although maize is grown in most parts of Kenya, this study focused on four project regions namely: Western Kenya, South Rift, Central Highlands, Upper Eastern and Lower Eastern (Figure 1), where DroughtTEGO® commercialization activities were implemented. Partly due to logistical and statistical considerations, the decision was taken to interview proportionate maize farmers in each of the five focus regions, giving 642 maize farmers. The number of farmers interviewed in each region was determined by the maize production statistics in the area and the population. Within the regions, one to two counties were selected randomly (Table 1) for the study.

Probability Proportional to Size (PPS) sampling technique using the number of counties per region as strata was applied to arrive at sample size per region. Within each identified county, a sub-county was randomly sampled. At the regional level, farmers were sampled from sub-counties with significant maize production based on figures from the statistical unit of the Ministry of Agriculture, Livestock and Fisheries (MoALF) and AATF. In some instances, due to unavailability of sampling frames, the households were randomly sampled through random transect walks. At the sub-county level, one administrative location was selected purposively, and villages selected with the help of AATF field staff and county

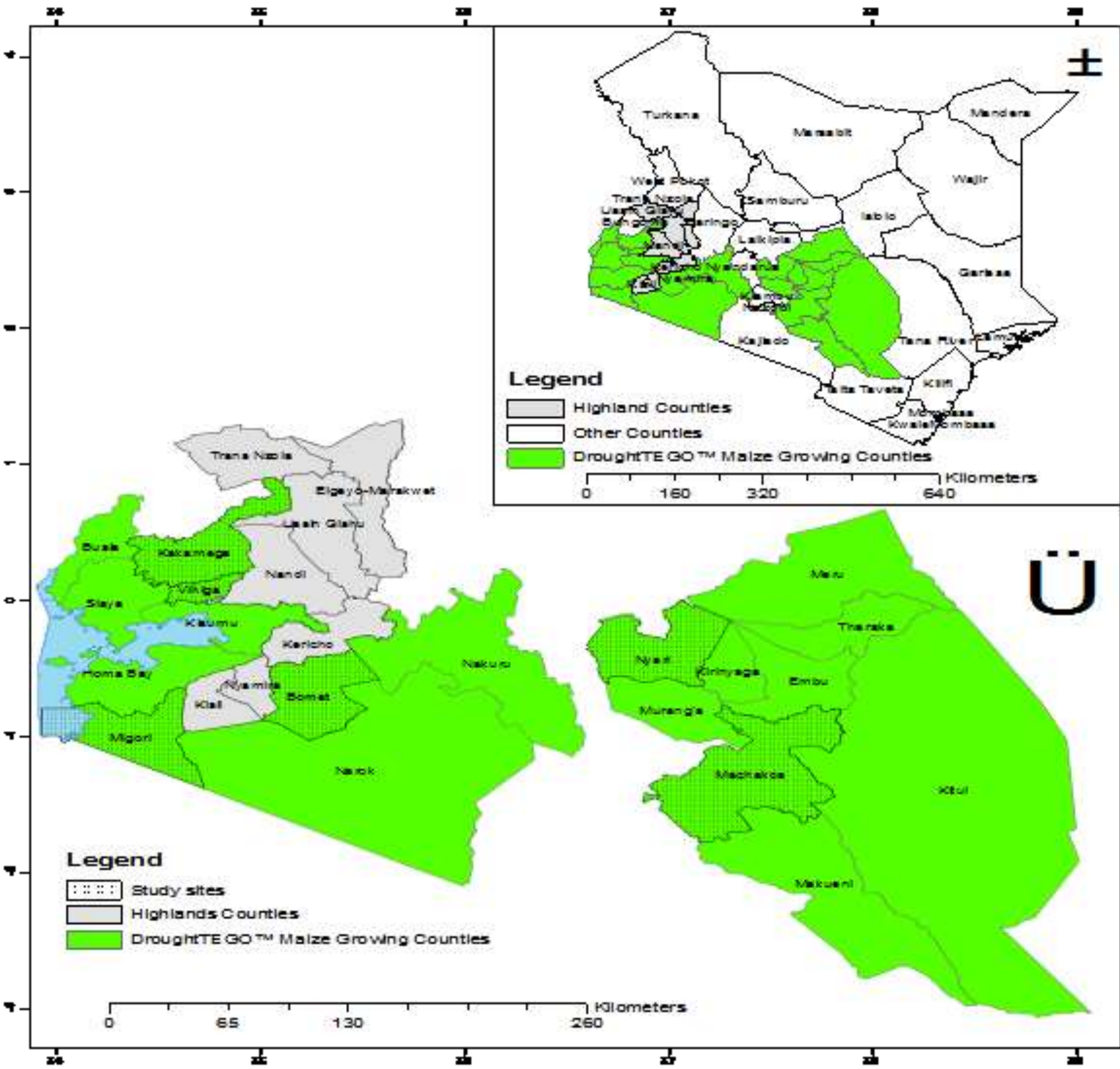

Figure 1. Map showing the DroughtTEGO® growing counties and the study area sites.
Source: This study (2017).

officials. To enhance data validity and reliability, intensively trained enumerators using a questionnaire developed by the researcher interviewed farmers. The interviews were conducted in January 2017. To maintain uniformity, data from all regions were transmitted to a host server where they were checked daily. The study utilized the Open Data Kit (ODK) whereby data was collected on a mobile device and transmitted to an aggregation server. The household-level data collected included gender, age and education level of farmer, household size, and membership to a farmers' organization. Additional information collected was accessibility to extension services, and knowledge of varieties planted by each farmer. Farm-level variables collected included size of the farm, crops grown, soil quality, distance of irrigation water source, type of maize seeds used by farmers, access to information on DroughtTEGO® maize seeds, methods of technology transfer; and advantages and drawbacks of using DroughtTEGO® maize seeds, food consumption and food security; and perceptions of changes in farm productivity and income.

Global Positioning System (GPS) was used to capture the precise location/coordinates of the sampled households and hence digitally mapped all the households/villages visited in the survey. Key stakeholders consulted included county officials, MoALF staff, AATF field staff, farmers hosting maize demonstration sites and agro-dealers.

Conceptual framework

The basic question in impact assessment is whether observed differences in maize income, total household income and poverty levels between adopters and non-adopters could be attributed to the use of DroughtTEGO® maize hybrid seeds. This situation cannot be directly observed at household level, but it is possible to approximate it by constructing an appropriate counterfactual. This

Table 1. Regional distribution of DroughtTEGO® adoption by farmers in four regions in Kenya

Region	Counties	Sampling sub-counties	Sample size based on county proportion
South Rift	Bomet	Bomet	102
Western	Vihiga	Sabatia	75
	Migori	Rongo	135
	Kakamega	Kakamega	60
Central Lower Eastern	Nyeri	Mukurweini	170
	Machakos	Kangundo	100

Source: This study (2017).

study addresses this issue of counterfactual using propensity score methods (PSM). The basic concept behind the PSM is to match observable characteristics of both adopters and non-adopters according to the estimated propensity score (Köhler et al., 2016). The prominent features of the PSM are the ability to create conditions of randomized experiment designs to evaluate a causal effect as in a controlled experiment. The idea is to compare individuals who, based on observables, have a very similar probability of receiving treatment (similar propensity score), but one of them received treatment and the other did not, i.e. PSM constructs comparison groups by matching every individual household observation of adopters with an observation household with similar characteristics from the group of non-adopters.

The PSM have several useful features: no baseline data are required. It ensures comparison of the outcome variables between adopters and non-adopters that have overlapping or similar observable characteristics as predicted by propensity scores (Dehejia and Wahba, 2002). It takes covariates to be independent of the use of the technologies under consideration when comparing sample of the population of households with similar characteristics allowing causal interpretation of the results. Unlike the Heckman and instrumental variable (IV analytical frameworks), PSM does not require either distributional, parametric or linearity assumptions because the model assumes that the conditions set in matching the observable characteristics eliminate sample selection bias (Heckman and Navarro-Lozano, 2004). Again, the PSM approach has added advantage as compared to commonly used impact assessment methods that suffer from what is referred to either as overt, hidden biases or non-compliance.

Overt bias occurs due to differences in observable characteristics between adopters and non-adopters not caused by technology adoption. Hidden bias, on the other hand, occurs due to unobservable characteristics that are inherent. Non-compliance, also referred to as endogeneity in econometrics, arises because the adoption of a variety is a farmer choice and we cannot assign treatments randomly.

Analytical model

Let $P_i = 1$ denote a dummy variable such that the i^{th} household adopts DroughtTEGO® seeds and $P_i = 0$ otherwise. Similarly let Y_{1i} *and* Y_{2i} denote potential observed outcomes (maize income, total household income, and poverty indices) for adopter and non-adopter units, respectively. Therefore, $\Delta = Y_{1i} - Y_{2i}$ is the impact of the technology on the i^{th} household, called treatment effect.

However, because we only observe $Y_i = P_i Y_{1i} + (1 - P_i) Y_{2i}$ rather than Y_{1i} *and* Y_{2i} for the same household, it is apparent that we cannot compute the treatment effect for every individual. Thus, the primary treatment effect of interest is given by:

$$\pi = E(Y_{1i} - Y_{2i} / P_i = 1) \tag{1}$$

This is commonly referred to as the average effect of the treatment on the treated (ATT). Following Rosenbaum and Rubin (1983), the propensity score (PS) can be estimated as:

$$PS(X) = PS(Y_i = 1 / X) \tag{2}$$

Where X is a vector of pre-treatment covariates, which include variables that affect both adoption and outcomes variables. These variables are listed in Table 2 as dependent and independent variables.

The ATT can then be estimated as:

$$\begin{aligned} \pi &= E(Y_{1i} - Y_{2i} / P_i = 1) \\ &= E\left[E(Y_{1i} - Y_{2i} / P_i = 1, PS(X))\right] \\ &= E\left[E(Y_{1i} / P_i = 1, PS(X)) - E(Y_{2i} / P_i = 0, PS(X))\right] \end{aligned} \tag{3}$$

According to Smith and Todd (2005), matching should be conducted on variables that influence both treatment assignment and outcomes and should not be affected by the treatment. Hence, the independent variables used in our case are as the ones used in the adoption models. In general, a larger set of variables is preferred to reduce the effects of unobservable variables. These variables are used to find a suitable counterfactual group, that is, given the outcome variable for household who uses the improved technology, the model allows a comparison with the same outcome variable for household that did not use the technology but has very similar characteristics (independent variable). A probit model was applied however; in principle, any discrete choice model can be used.

Several matching methods can be utilized to match adopters with non-adopters with similar propensity scores. These matching methods include Nearest Neighbor Matching (NNM), Caliper and Radius Matching (CRM), Kernel-Based Matching (KBM), Local Linear Matching (LLM), spline matching and Mahalanobis distance matching estimators. The basic idea is to numerically search for closest "neighbors" of adopters that have a propensity score that is very close to the propensity score of the non-adopters and vice-versa. The most commonly applied matching estimators are NNM, CRM and KBM methods. In our case, NNM and CRM are utilized.

Table 2. Variables description for DroughtTEGO® varieties adoption studies.

Variable	Units	Definition
Treatment variable		
ADOPT	Dummy	1, if household adopted any DroughtTEGO® varieties; 0, otherwise
Outcome variable		
MAINCOME	$USD/kg	Total maize income per kg of seed used
TOINCOME	$USD	Total household annual gross income
HEADCOUNT	Number	1, if household per capita income is below poverty line; 0, otherwise
POVERTYGAP	$USD	Difference from/to the poverty line
Independent variables		
Demographic characteristics		
AGE	Year	Age of household head (years)
AGESQ	Year	Age of household head squared (years)
EDUCATION0	Dummy	1, Household head with no formal education; 0, otherwise
EDUCATION1	Dummy	Household head with primary education; 0, otherwise
EDUCATION2	Dummy	Household head with secondary education; 0, otherwise
EDUCATION3	Dummy	Household head with > secondary education; 0, otherwise
GENDER	Dummy	1, if the household head is male; 0, otherwise
HHSIZE	Number	Number of family members living in the household in adult equivalent (count)
FARMWORKER	Number	Number of adults working in the farm (count)
DRATIO	Number	Dependency ratio (proportion over 64 and under 18years of age (%)
Access to information		
EXTENSION	Dummy	1, if main source of information is government extension; 0, otherwise
FARMER	Dummy	1, if main source of information is another farmer; 0, otherwise
DEMOS	Dummy	1, if main source of information demonstration and field trials; 0, otherwise
RADIO	Dummy	1, if main source of information is radio; 0, otherwise
Asset endowment		
FARMSIZE		Farm size (ha)
Other variables		
RECORD	Dummy	1, if the household keeps farm records; 0, otherwise
WOMEN	Dummy	1, if women control household resources; 0, otherwise
FOODSEC	Rate	Rating of food security in the last 1 years
PRICE	Dummy	1, if farmer perceives the DroughtTEGO® seed to be expensive; 0, otherwise
County dummies		
Bomet	Dummy	1, if the farmer is in Bomet; 0, otherwise
Vihiga	Dummy	1, if the farmer is in Vihiga; 0, otherwise
Migori	Dummy	1, if the farmer is in Migori; 0, otherwise
Kakamega	Dummy	1, if the farmer is in Kakamega; 0, otherwise
Nyeri	Dummy	1, if the farmer is in Nyeri; 0, otherwise
Machakos	Dummy	1, if the farmer is in Machakos; 0, otherwise

Source: Survey results (2017).

Nearest neighbor, matching method matches adopters with non-adopter with the nearest propensity scores. However, NNM faces the risk of bad matches, particularly if the closest neighbor is far away. To overcome this problem one can use the second alternative matching algorithm called CRM matching. Caliper and radius matching use a tolerance level on the maximum propensity score distance (caliper) to avoid the risk of bad matches. Essentially, all matching methods should give the same or similar results, but in practice one must consider trade-offs in terms of bias and efficiency with each method.

Variables

The dependent variable is a dummy variable that take value one (1) if household planted any DroughtTEGO® varieties and the value zero (0) if none was planted. The outcome variables of interest in this study are maize income (MAINCOME), total household income

(TOINCOME) and poverty indicators.

Maize income per kilogram of maize seed planted (MAINCOME) is taken to be a proxy for agricultural productivity. This is because most of the farmers in the study regions plant several crops in one plot (intercropping) making it complex and hard to quantify area allocated for maize production. Farmers intercrop maize with other crops such as beans, pigeon pea, groundnuts, cowpeas, sweet potatoes, soybeans, nappier grass, among others. Maize income was calculated as total maize revenue minus variable costs divided by amount of seed planted (maize income in $USD/kg).

Total household income (TOINCOME) was calculated as the value of all household production arising from both crop and animal production, minus variable costs and off farm income. The Foster-Greer-Thorbecke poverty index (FGT) is used in the analysis of the headcount poverty index (HEADCOUNT) and the poverty gap (POVERTYGAP). The below FGT poverty formula was utilized:

$$P_\alpha = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{z-y_i}{z}\right]^\alpha \; P_\alpha = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{z-y_i}{z}\right]^c \quad (4)$$

Where, n is the number of households in the sampled population, z refers to the poverty line, y is the per capita income for the ith person. α is the poverty aversion parameter, α ≥ 0 which takes values 0, 1 and 2 for poverty incidence, poverty depth and poverty severity, respectively. When α = 0, Pα gives the incidence of poverty (HEADCOUNT) or the proportion of people that are poor. When α = 1, then Pα gives the depth of poverty (POVERTYGAP) that is, the difference between per capita income per day to the poverty line. When α = 2, P α is a measure of severity of poverty and reflects the degree of inequality among the poor.

A dummy variable which takes the values 0 or 1 (denoting whether the individual/household income lies below the poverty line or not (that is, 'poor' = 1 and 0 otherwise) is used in the analysis. Due to none existence of poverty line income in Kenya, international standard of US$ 1.25/ capita/ day is used as a poverty line benchmark (World Bank, 2017). The per capita household income is calculated as the sum of total income divided by the number of household members.

Based on previous hypotheses from the literature, the independent variables utilized to find a suitable comparison group includes age of the household head and its square (AGE, AGESQ), education (EDUCATION), gender of the household head (GENDER), and dependency ratio (DRATIO). Labor availability is included by considering both available family labor (HHSIZE) and number of adult members working in the farm (FARMWORKER). Access to information on improved technologies is captured through contacts with extension officers (EXTENSION), other farmers as main source of information (FARMER), demonstrations (DEMOS), and RADIO variables. Lack of access to cash or credit can significantly limit the adoption of improved technologies hence asset endowment was included through total land size (FARMSIZE). Other variables included were record keeping (RECORD), food security in the last two years (FOODSEC), women control of the household resources (WOMEN), perception of seed prices (PRICE) and county dummies.

Before estimation, all the above variables were cross- checked for the commonly known econometric problems such as multi-collinearity done through the simple correlation matrix and variance inflation factor (VIF). VIF were by far less than 10, indicating that correlation between explanatory variables could not affect the results. An absolute value close to one means that strong correlation exists. VIF value of greater than 10 is an indication of potential serious multicollinearity (Ringle et al., 2015). Similarly, for endogeneity checks none of the independent variables was suspected to be explained within the equation it was utilized.

To ensure the robustness of the estimated average effect, the sensitivity of the estimates to hidden bias was conducted using the Rosenbaum bounds test. Plausibility of the covariates was also assessed by re-estimating the propensity score on the matched sample, for adopters and matched non-adopters and pseudo-R^2 was then compared to that of before and after matching. Again, the distribution of the estimated propensity scores before and after the matching was plotted for visual assessment. Differential adoption by county was also assessed to account for perceived heterogeneous impacts at county level.

RESULTS AND DISCUSSION

Descriptive statistics

Average maize net income was computed at 49.96 $USD/ 90kg (Ksh 4,996/ kg), where the adopters had 82% significantly higher income than the non-adopters (Table 3). Again, the comparison between adopters and non-adopters on total household income also showed that adopters reported statistically higher net income (21%) as compared to their counterpart.

Based on the poverty line, the average poverty headcount was 0.83, implying that 83% of the households in the study area lived in dire poverty. Non-adopters were relatively poorer than the average, with poverty headcount higher by 1% point, thus adopters were less poor than the non-adopters were. A closer look at the data showed extremely high poverty rate in Migori (94%), while the lowest poverty rate was observed in Nyeri (70%).

Results further indicate that 26% of the maize farmers adopted 1–6 DroughtTEGO® maize varieties. However, after accounting for the non-exposure bias arising from the farmers who were not aware of these varieties, the adoption rate rose to about 42%.

Significant difference at 1% was found between DroughtTEGO® adopters and non-adopters regarding age, indicating that adopters are relatively older than their non-adopters by 4%. This finding suggests that DroughtTEGO® adoption was positively correlated with age. Older farmers are more likely to use improved technologies when age is taken as a proxy for experience. In this case, it is assumed that with age farmers get more experience with new technologies and are likely to adopt the new technologies more efficiently. However, there is a certain age beyond which, farmers' ability to take risk and engagement to unknown technologies and innovations tend to decrease. Age of the household head in other studies does not show a consistent pattern in this regard on technology adoption (Rogers, 2003).

Quite interesting was the insignificant difference between adopter and non-adopter regarding levels of education, suggesting that DroughtTEGO® adoption was uncorrelated with education. Some studies have shown that education is highly associated with timing of adoption rather than with the technology adoption itself (Weir and Knight, 2000).

Table 3. Characteristics of DroughtTEGO® varieties adopters and non-adopters, summary statistics before matching in Kenya.

Variable	Full sample n = 642		Non-adopters n = 476		Adopters n = 166		Difference
	Mean	S. E	Mean	S. E	Mean	S. E	
Outcome							
MAINCOME	49.96	3.84	38.08	3.88	69.29	7.45	31.11***
TOINCOME	680.33	45.22	641.43	45.61	773.61	107.85	133.25**
HEADCOUNT	0.82	0.02	0.83	0.02	0.82	0.03	0.02
POVERTYGAP	-0.28	0.05	-0.29	-0.05	-0.26	-0.13	-0.03
Independent							
AGE	49.40	0.55	48.89	0.66	50.88	0.98	-2.00*
AGESQ	2,634.42	56.56	2,594.82	67.67	2,747.71	100.89	-152.89
EDUCATION0	0.08	0.01	0.08	0.01	0.06	0.02	0.02
EDUCATION2	0.47	0.02	0.45	0.02	0.51	0.04	-0.05
EDUCATION2	0.34	0.02	0.34	0.02	0.33	0.04	0.01
EDUCATION3	0.11	0.01	0.12	0.10	0.02	0.02	0.02
GENDER	0.83	0.01	0.82	0.02	0.87	0.03	-0.06*
HHSIZE	5.96	0.23	5.67	0.25	6.79	0.29	-2.22**
FARMWORKER	2.28	0.06	2.23	0.06	2.72	0.23	-0.58***
DRATIO	42.45	2.02	42.93	2.23	42.06	2.83	2.86
EXTENSION	1.00	0.00	1.00	0.00	1.00	0.00	
FARMER	0.39	0.02	0.43	0.02	0.27	0.02	0.17***
DEMOS	0.11	0.01	0.09	0.01	0.18	0.01	-0.09***
RADIO	0.05	0.01	0.04	0.01	0.08	0.02	-0.04*
FARMSIZE	2.28	0.09	2.26	0.11	2.35	0.19	-0.09
RECORD	0.11	0.01	0.09	0.01	0.17	0.03	-0.09***
WOMEN	0.59	0.02	0.59	0.02	0.60	0.04	-0.01
FOODSEC	1.75	0.04	1.58	0.04	2.22	0.07	-0.63***
PRICE	0.06	0.01	0.05	0.01	0.08	0.02	0.04*
Bomet	0.16	0.01	0.18	0.02	0.10	0.02	0.08***
Vihiga	0.12	0.01	0.08	0.01	0.23	0.03	-0.15***
Migori	0.21	0.02	0.22	0.02	0.19	0.03	0.03
Kakamega	0.09	0.01	0.04	0.01	0.23	0.03	-0.19***
Nyeri	0.26	0.02	0.28	0.02	0.22	0.03	0.06*
Machakos	0.16	0.01	0.20	0.02	0.04	0.01	-0.16***

SE - robust standard errors, statistically significant at the 0.01 (***), 0.05 (**), 0.10 (*) level of probability (t-test are used for differences in means).
Source: This study (2017).

The data also indicated that there were significant differences in terms of gender, with about 87% of the adopters being male headed households as compared to 82% of the non-adopters. It is generally, acknowledged that male-headed households have more likelihood of getting information about new developments and are more likely to take on risky businesses as compared to their female-headed counterparts.

As expected, adopters had a significantly higher active family labor force than the non-adopters as indicated by the family size (20% higher) and number of adults who work in the farm (27% higher). This may imply timeliness in activities such as planting, weeding and harvesting, which are normally done at times of peak demands. Additionally, it could imply that the higher the number of persons per household, the more numbers of mouths to feed and the more likelihood to adopt new techniques likes the use of drought tolerant varieties to guarantee better production.

Similarly, adopters also extensively kept records (17%) as compared to non-adopters (9%). In general, record keeping of production activities enables a farmer to increase profits through better farm planning and early identification of problems in the production chain. We

Table 4. Probit estimates of the propensity score matching for DroughtTEGO® varieties adoption studies.

Variable	CRM matching		NNM matching	S.E.
	Estimated coefficients	S.E.	Estimated coefficients	
AGE	0.00	0.01	0.00	0.01
EDUCATION1	0.55	0.41	0.55	0.41
EDUCATION2	-0.01	0.38	-0.01	0.38
GENDER	0.23	0.41	0.23	0.41
HHSIZE	-0.01	0.05	-0.01	0.05
FARMWORKER	0.30	0.11***	0.30	0.11***
DRATIO	0.01	0.01**	0.01	0.01**
EXTENSION	-1.18	0.50*	-1.18	0.50*
FARMER	-0.65	0.36*	-0.65	0.36*
DEMOS	-0.34	0.42	-0.34	0.42
RADIO	0.20	0.48	0.20	0.48
FARMSIZE	0.01	0.08	0.01	0.08
RECORD	0.02	0.34	0.02	0.34
WOMEN	0.14	0.28	0.14	0.28
FOODSEC	0.21	0.80	0.21	0.80
PRICE	0.13	0.61	0.13	0.61
BOMET	-1.63	0.52***	-1.63	0.52***
VIHIGA	-0.09	0.40	-0.09	0.40
MIGORI	-1.17	0.40***	-1.17	0.40***
NYERI	-0.68	0.41*	-0.68	0.41*
Constant	-1.65	1.17	-1.65	1.17
Summary statistics				
McFadden R^2	0.22		0.22	
Model chi-square	41.80 ***		41.80 ***	
Log likelihood ratio	-75.54		-75.54	

SE - robust standard errors, statistically significant at the 0.01 (***), 0.05 (**), 0.10 (*) level of probability (t-test are used for differences in means).
Source: This study (2017).

observed significant differences in the source of information; particularly those who accessed through neighboring farmers' demo sites and radio were higher amongst adopters than the non-adopters were. Information about a new technology is a prerequisite for adoption. Information generally improves understanding, reduces the uncertainty about new technologies, and can change individual's perception from subjective to objective assessment.

We uncovered no significance difference in farm size between the adopters and non-adopters; suggesting that adoption of DroughtTEGO® is not dependent on farm size. However, this contrasts with the findings of Diagne and Demont (2007) who reported a significant difference between technology adopters and non-adopters in terms of farm size. It is important to note that the current study targeted small-scale farmers, the majority of whom have small land holdings (2.28 acres on average). For this reason, one should not expect highly significant differences in land size between adopters and non-adopters.

However, it is essentially important to remember that these comparisons of mean differences may not be the result of technology adoption, but instead may be due to other factors, such as differences in household characteristics, which may confound the impact of the technologies on the said outcome variables (Macharia et al., 2013). Additionally, because adoption is endogenous, that is a factor in a causal model or causal system whose value is determined by the states of other variables in the system contrasted with an exogenous variable, no causal interpretation could be done at this point. Therefore, further analysis was conducted (Table 3).

Propensity scores estimations

The results of the propensity score matching are reported in Table 4. As indicated earlier, the propensity scores procedure only serve as a framework for balancing the observed distribution of covariates across the treated and the untreated groups. In general, the results are consistent with our expectations and the models fit the data reasonably well. The models also have good explanatory powers (Table 4).

Among the covariates, number of people working on the farm, dependency ratio, government extensions and other farmers being the main source of information of new seeds, among others, were statistically associated with propensity to adopt DroughtTEGO® maize hybrid seed. In contrast, important variables, such as age of household head, dummy for level of education, and farm size were not related to DroughtTEGO® hybrid maize adoption. The distribution of the propensity scores and the region of common support were plotted; most of the treatment households are on the right side, while most of untreated (control) households are on the left side of the distribution (Figure 2). In general, the graph shows that there was substantial overlap and similarity among the adopters and non-adopters. Thus, the common support condition imposed satisfies the balancing property.

Table 5 reports results from covariate balance testing before and after matching procedure. It is important to note that the probability values of the likelihood ratio tests failed to reject the joint significance of covariates before matching. However, after matching it is rejected, an indication that the specification of the propensity score estimation process was successful. The pseudo-R^2 also dropped significantly from 23% before matching to about 10-12% after matching, suggesting that the matching procedure was successful in terms of balancing the distribution of covariates between the adopters and non-adopters (Sianesi, 2004).

Impact of DroughtTEGO® hybrid using AVERAGE ADOPTION EﬀECT

Evidence from findings reveals that different matching algorithms produce different quantitative results, but the qualitative findings were similar (Table 6). The results indicate that the use of DroughtTEGO® hybrids significantly increased maize income, total household income by 75-82% and reduced poverty gap from 0.54 $USD (Ksh 54) to 0.8 $USD (KSh 80). The nearest neighbor based matching technique gives the highest maize income differentials of 49%, whereas the radius-based matching gives the lowest value (39%). Similarly, adoption increases total income by about 45% and reduces the depth of poverty by about 51 point using radius estimators. Deeper analysis indicates high and positive correlation between maize income and total household income (0.54) supporting the idea of poverty reduction. However, it is important to note that though the adoption of DroughtTEGO® hybrid reduces the depth of poverty, it hardly helps them in the short-term, within three years of adoption, to move beyond the poverty line as no statistically significant effect could be observed on poverty head count.

The above findings are consistent and in tandem with reported studies of impact of modern crop varieties on household welfare. For example, studies by Hossain et al. (2006) and Mendola (2007) in Bangladesh, Janaiah et al. (2006) in India and Wu et al. (2010) in China all indicated that the adoption of improved crop varieties had a significant negative impact on poverty status. Study by Becerril and Abdulai (2010) found significant increase in per capita expenditure and reduced poverty by improved maize adopters in Mexico. Kijima et al. (2008) also showed that NERICA rice adoption reduces poverty, without decline in income distribution, in Uganda. Tiwari et al. (2010) found that maize varietal interventions in Nepal increased food availability with greater benefits going to poor farmers compared to their rich counterparts. To get more understanding of the impact of DroughtTEGO® use on diﬀerent groups of adopters, we also examined the diﬀerential impact of adoption based on county. The analysis is based on matched samples obtained from nearest neighbor matching estimators. These results showed that some opposite effects were observed among counties, which were not visible in the overall sample average. The effects on maize incomes were higher for the DroughtTEGO® hybrid users across the counties, except in Bomet and not statistically different in the case of Machakos. In terms of total income, only Nyeri and Kakamega showed significant gains while adopters seemed to get similar income in other counties. With respect to poverty reduction, the picture is clear in that it seemed adopters were above poverty line except in Vihiga, hence the overall non-significant effect of adoption on head count was linked to this county.

Farmers perception of change in the household's food security

During the survey, attention was paid to the perception of change in the household's food security over the three years of technology commercialization. Overall, a larger number of households reported improved rather than worsened food security (Figure 3). DroughtTEGO® adopters had a higher proportion (54%) of households indicating that their food security had improved over the last three years, as compared to their non-adopters (22%). Similarly, the percentage of households that reported worsened food security was higher for non-adopters (63%) and the difference was statistically significant at p value of 0.005. The above results were well backed-up by the maize income, which was 81% higher for adopters compared to non-adopters (Table 6). These positive results could be due to the adoption of the

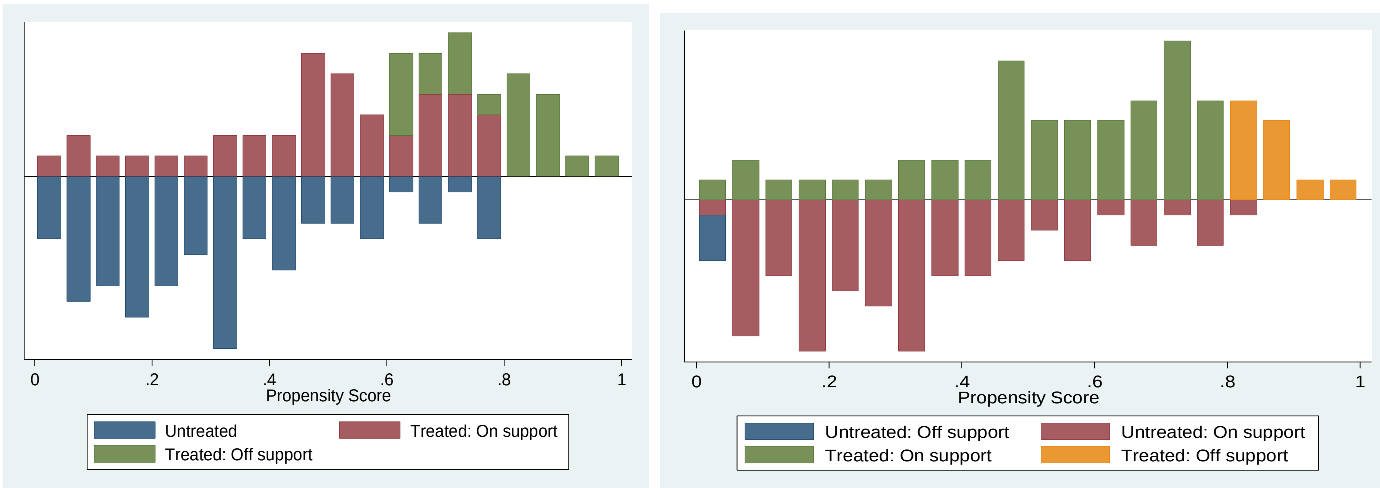

Figure 2. Propensity score distribution and common support for CRM and NNM propensity score estimation[1] respectively.
Source: This study (2017).

Table 5. Matching quality indicators before and after matching for DroughtTEGO® varieties adoption studies in Kenya.

Matching algorithm	Pseudo R^2		LR X^2(p – value)	
	Before matching	After matching	Before matching	After matching
CRM	0.23	0.10	45.05 (p = 00)***	11.53 (p = 0.93)
NNM	0.22	0.12	41.80 (p = 00)***	15.98 (p = 0.72)

SE - Robust standard errors, statistically significant at the 0.01 (***), 0.05 (**), 0.1 (*) level of probability (t-test are used for differences in means).
Source: This study (2017).

Table 6. Maize income, total household income and incidence of poverty after matching.

Method	Outcome	Measurement	Adopters	Non- adopters	Difference=average treatment effect on the treated (ATT)
CRM	MAINCOME	$USD	79.76	48.57	31.19**
	TOINCOME	$USD	912.97	504.83	408.14*
	HEADCOUNT	%	0.85	0.92	-0.07
	POVERTYGAP	$USD	-0.04	-0.56	0.51*
NNM	MAINCOME	$USD	79.47	39.42	40.05**
	TOINCOME	$USD	889.04	524.45	364.59*
	HEADCOUNT	%	0.86	0.92	-0.06
	POVERTYGAP	$USD	-0.12	-0.52	0.40*
AVERAGE	MAINCOME	$USD	79.62	43.99	35.62**
	TOINCOME	$USD	901.00	514.64	386.36*
	HEADCOUNT	%	0.86	0.92	-0.07
	POVERTYGAP	$USD	-0.08	-0.54	0.46*

SE - robust standard errors, statistically significant at the 0.01 (***), 0.05 (**), 0.10 (*) level of probability (t-test are used for differences in means).
Source: This study (2017).

[1] Treated on support indicates the individuals in the adoption group who find a suitable match, whereas treated off support indicates the individuals in the adoption group who did not find a suitable match and Untreated indicates non-adopters.

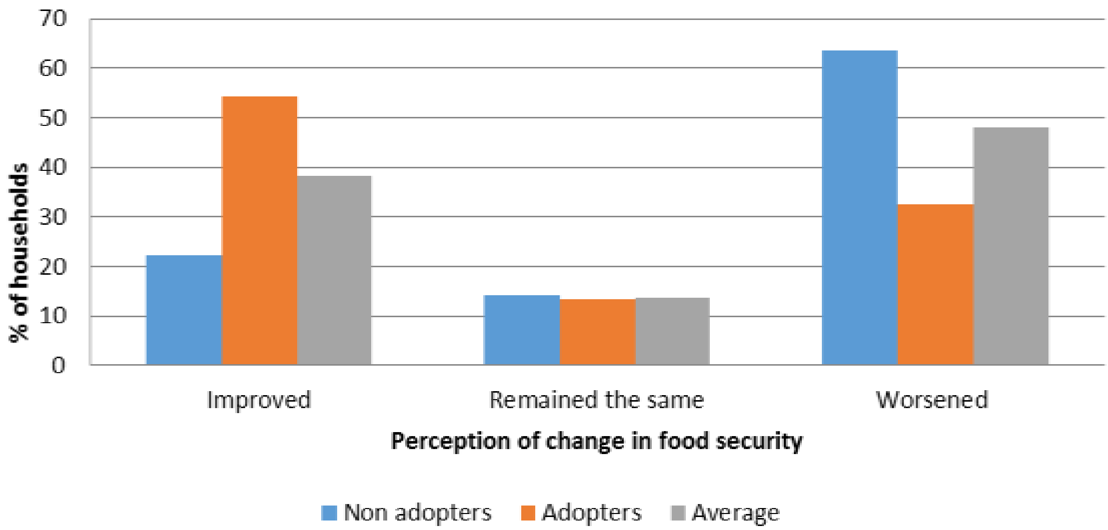

Figure 3. Perception of change in food security over the previous three years.
Source: This study (2017).

drought tolerant maize seed under promotion, supporting the widely held view that adoption of technologies is crucial to food security and poverty alleviation in rural areas of developing countries. In most African settings, a household is considered food secure if it has enough of the popular staple food.

CONCLUSION AND POLICY IMPLICATIONS

Our findings demonstrate a direct causal link on total household income, maize income and poverty status from adoption of DroughtTEGO® maize varieties in rural Kenya. The PSM techniques used in the analysis allowed us to construct an adequate counterfactual for the comparison of farmers according to their adoption status. The causal impact estimation from PSM showed, among other things, that the use of DroughtTEGO® seeds had the potential to increase maize income by 81%, total household income by 75% and reduce the depth of poverty by 46-point margins. Nevertheless, the magnitude of this effect was not yet enough to lift these farmers' above the poverty line in the short-term of three years, hence no change in poverty headcount was observed. Notable findings differentiated by County showed that maize income gains were more pronounced in Vihiga, but it hardly helped them to overcome the poverty line due to large household sizes.

These findings suggest that the use of DroughtTEGO® might have a role in improving household wellbeing through the increase of agricultural income and consequently ability to escape poverty. The study recommends the formulation and implementation of appropriate policies that could improve the adoption of DroughtTEGO® hybrid maize varieties. Further analysis with panel data captured over several years will also be useful to measure the actual change in poverty levels that could be attributed to DroughtTEGO® varieties adoption.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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