The effect of technological packages on maize productivity in Ecuador

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Abstract

This article analyzes the effect of adopting hybrid maize on productivity per hectare, using data obtained from 1,622 producers in Ecuador. Special attention is given to examining whether there are differences between producers who adopted maize independently and those who did so through a technological package –partially subsidized by the state– which, in addition to hybrid seed, included complementary technologies, training, and technical assistance. The findings show that adopting hybrid seed had a positive impact on productivity per hectare, regardless of whether it was adopted independently or as part of a technological package. However, producers who adopted the technological package clearly saw the greatest increase in productivity.

Keywords: agricultural technology; technological packages; productivity; agricultural producers; hybrid maize.

1. INTRODUCTION

In developing countries, the farming sector is largely characterized by the presence of small producers which use traditional techniques and seeds with a lower yield (Lacki, 2011). This explains why the productivity index when comparing modern and traditional farming was 2000 times greater at the beginning of the century (Carrillo, 2014). According to the literature, in developing countries low adoption rates are due to the fact that the new technology not only depends on available resources, but also on other factors related to incomplete or erroneous information, risk, uncertainty, institutional restrictions, human capital of those who adopt it, the availability of consumables and problems related with the quality of infrastructures (Foster and Rosenzweig, 1996; Kohli and Singh, 1997).

Facing this situation, governments in their desire for correcting the low levels of farming productivity establish subsidies so that small producers can acquire a variety of new of seeds (Todaro and Smith, 2012). In many cases, such subsidies are applied to technological packages which, in addition to higher yield seeds, include other consumables (fertilizers, pesticides, rooting agents, etc.), as well as technical support on how to produce with these new varieties. This is done with the goal of providing farmers with the complementary knowledge and assets needed so that the adoption of new seeds effectively translates into increased productivity. In this regard, there is extensive literature which highlights that companies which acquire new technologies, but do not invest in complementary technologies or do not carry out changes in their technical training or productive organization, have a lower probability of generating competitive advantages compared to those who do (Ouadahi, 2008; Boothby *et al*., 2010). Nevertheless, in spite of the fact that the technological packages exist, there are still producers who still use traditional seeds, as well as farmers who adopt new seeds without turning to technological packages.

Within this context, this article has as its objective to analyze if the effect of adopting hybrid maize seeds on productivity per hectare differs between farmers who adopted them independently and those who turned to technological packages. It should be expected that producers who turn to technological packages, which in addition to new seeds include complementary supplies and technical training, make a more efficient use of the seeds and as such have a greater productivity per hectare. As a result, this research not only presupposes a contribution at the moment of presenting evidence on the effect of adopting hybrid maize on productivity per hectare in the case of Ecuador, but also to provide evidence on whether the effects of adoption are dependent on the existence of complementary technology and knowledge provided by the technological packages.

This is why we delved into the data from the Ministry of Agriculture and Livestock (MAG)[1] corresponding to 2015 and 2016 with a total of 1,622 producers of flint maize, found in the four primary maize producing Ecuadorian provinces: Los Ríos, Guayas, Manabí and Loja. Even though flint maize is produced in practically the whole country, more than 90% of the land harvested is found in the aforementioned provinces (SIPA, 2020). The Ecuadorian case turns out to be ideal for analyzing the effect of technological farming packages given that during the years 2015 and 2016 the government subsidized a technological package for adopting hybrid maize seeds which, in addition to the seeds, included compound fertilizers (nitrogen, phosphate, potassium), pesticides, phytosanitary and rooting products. At the same time, they offered technical support, training and follow-up during the six months which started with planting all the way until the harvesting phase. Said package was called *seed kit* (kit semilla).

In order to calculate the effect of adopting hybrid seeds on productivity per hectare, selection bias is controlled. This is due to the adoption of the hybrid seed, be it independently or through the technical package, not being random but dependent on the farmers' other characteristics which could also influence productivity per hectare. We used the propensity score matching (PSM) method to compare the results, comparing the results of the nearest neighbor and Kernel matching algorithms.

The rest of the article is organized in the following manner: the second section reviews the literature on technology adoption and its effects, at the same time that it shows empirical evidence of the effects of adopting hybrid maize. The third section presents the data, variables and methodology employed, while the fourth section discusses the implications of the empirical results. Finally, the fifth presents the conclusions.

2. REVIEWING THE LITERATURE

In general terms one can identify two schools of thought which take on the problem of technological adoption (Ruttan, 1996). On the one hand, the orthodox school considers technological adoption to be characterized by a rational selection process by which the producer compares the benefits derived from the adoption and the acquisition costs. It assumes that producers are always capable of selecting the technology which most behooves them (Ruttan, 1996). On the other hand, the evolutionist school points out that technological adoption should not be considered as a rational selection (Selis, 2000), given that the agents make the decision within an environment characterized by complete uncertainty. In this regard, evolutionist models consider the process of technological adoption as influenced by other factors beyond economic ones. As such, in order to adopt a new technology, among other factors, it is also necessary to have complementary technologies and knowledge necessary to operate it efficiently (Teece, 1986 and 1988). This makes it so that training and organizational change is critical for the adoption of new technologies to generate greater gains in productivity (Bootchby *et al.,* 2010). Specifically, this is the process of adopting new technology influences, not only economic factors, but also technological, institutional and individual ones (Foster and Rosenzweig, 1996; Kohli and Singh, 1997).

The economic characteristics of producers influence the adoption of new technologies as those with greater resources, who have greater access to credit and have more land will be more prone to adopting new technologies (Feder and Umali, 1993). While from the target technological factor approach, the relative advantage of new technology in the economy stands out (Mwangi and Kariuki, 2015). There is evidence along these lines that the perception and knowledge farmers have of the characteristics of a new type of rice positively influences its adoption (Adesina and Zinnah, 1993). In other words, the farmers' knowledge and experience positively influences the adoption of new technologies. As such, a more experienced producer or one with greater education can have less uncertainty with regards to how new technology will perform and be more likely to adopt it without any problems (Rogers, 1971). Other technological factors, such as the existence of complementary technologies, are also determinants in the adoption of technology (Teece, 1986).

Institutional factors, for their part, also influence the adoption of new technology, given that social capital facilitates and propagates technological information exchange (Mignouna *et al.,* 2011). Another institutional factor that stood out is the presence of "agents of change" given that they are the ones in charge of informing producers of the existence of new technologies and how to properly take advantage of them. The agents act as a liaison between producers of new technology and their users. As such, greater contact with these agents accelerates the adoption process (Nazziwa-Nviiri *et al*., 2017). Other institutional characteristics are the laws and regulations which influence the market, as well as transportation and communication infrastructures (Mwangi and Kariuki, 2015; Nazziwa-Nviiri *et al*., 2017).

Studies on the adoption of farming technologies highlight that the farmer's own characteristics greatly influence their propensity to adopt new technologies. In this regard, there is evidence that the age of the producer negatively influences technological adoption, due to the fact that older producers tend to be more risk-averse (Mauceri *et al*., 2007; Pan, 2014; Mason and Smale, 2013). The size of the household can also affect technological adoption. On the one hand, larger households tend to have a greater available workforce, so they are more likely to adopt intensive labor technologies (Tiamiyu *et al*., 2009; Mauceri *et al*., 2007) but on the other, as Saín and Martinez (1999) state, households with more members will use a large part of their incomes to satisfy basic needs, and may have greater limitations at the time of acquiring new technologies.

As a consequence, adoption of farming technology is determined by a variety of factors, which also condition the benefits which the adopters can generate when taking advantage of the technology. That is why the performance of a new technology depends on the adopting party having complementary assets and knowledge (Boothby *et al.,* 2010). Complementary assets are those which are needed to generate value from investing in a new technology; that is to say that producers, in order to take advantage of the value of their investments in new technology need other investments, knowledge and assets which complement its proper functioning (Teece, 1986 and 1988). Consequently, acquiring new technology does not guarantee good performance, as some producers are not capable of adapting their production model to said technology. In this regard, there is ample empirical literature demonstrating that companies which acquire new technologies and simultaneously invest in complementary assets and training and implement organizational change in their productive model, tend to generate greater gains in productivity than those that do not (Grander, 2003; Bartel *et al*., 2007; Boothby *et al*., 2010). The main idea of said works is that gains in productivity resulting from technological adoption depend on adopting specific packages of new machinery and equipment, developing organizational change, as well as new skills (Boothby *et al.,* 2010).

Even though the benefits of adopting new farming technology is subject to extant complementary assets and technology, or rather other factors related to the behavior of agricultural prices, in general the empirical evidence demonstrates that adopters tend to fare better than those who do not adopt (Besley and Case, 1993; Doss and Morris, 2001; Mendola, 2007; Becerril and Abdulai, 2010). Regarding the effects of adopting hybrid maize, there are a variety of studies, which for the most part report that adoption had a positive impact on the well-being of farmers (Kutka, 2011; Olaniyan and Lucas, 2004; Lunduka *et al*., 2012; Khonje *et al*., 2015; Karim *et al*., 2010; Abate *et al*., 2016; Setimela *et al*., 2017; Bellon and Hellin, 2011). For example, using propensity score matching, Khonje *et al.* (2015) demonstrated that those who adopted hybrid seeds had greater yields, consumption and food security than those who did not. Becerril and Abdulai (2010) found that, in the Mexican states of Oaxaca and Chiapas, the adoption of hybrid maize had a positive impact on the well-being of households. There is also evidence on the positive impact had by hybrid maize adoption on the benefits of producers in Nigeria (Olaniyan and Lucas, 2004). Recently, Akhter *et al.* (2020), also through propensity score matching, presented evidence on the positive impact of hybrid maize adoption on production, household income and poverty reduction in Pakistan.

Though there is extensive empirical literature on the effects of adoption, no study analyzes the effects in Ecuador. Furthermore, as was already mentioned, we seek to analyze if the effect differs between farmers who adopted it independently, compared to those who turn to technological packages partially subsidized by the State. The primary interest of the study resides in analyzing its impact on productivity per hectare as it is one of the most used performance metrics in farming (Mason and Smale, 2013; Shively and Ricker-Gilbert, 2013; Tiamiyu *et al.*, 2009). Nevertheless, hybrid maize adoption could affect other measures of well-being for producers, independently of the effect on productivity per hectare. As such, the fact that we only present evidence regarding the impact on productivity per hectare does not mean that one should not extrapolate said effect to other measures of well-being for producers and their environment. In this regard, there is evidence that the use of improved seeds produces negative effects both for the producer as well as the environment. From the point of view of the producers, one can see that they might be affected negatively by the substitution of crops which are key for their personal nutrition (Shively and Ricker-Gilbert, 2013). From an environmental perspective, one can see that planting new varieties of maize could have a negative impact stemming from the use of agrochemicals and fertilizers, unsustainable irrigation systems, the introduction of genetically modified organisms, land erosion and deforestation (Nadal and Wise, 2019; Runge, 2002).

3. DATA, VARIABLES AND METHODOLOGY

The current investigation employs data provided by the General Organization for the National Information System (CGSIN)[2] of Ecuador's MAG in surveys carried out with 1,622 flint maize producers in the provinces of Los Ríos, Guayas, Manabí and Loja[3] , corresponding to the winter and summer planting for the years 2015 and 2016 (the data can be consulted at https://bit.ly/2wQgFR3). The database boasts information on economic factors (production, size of farm, area sown, etc.); technological factors (the use of hybrid seeds, use of fertilizer, use of machinery, type of crop, type of harvesting, the use of a technological kit, etc.); institutional factors (belonging to a farming association, possession of farming insurance, etc.) and factors specific to the producer (age, number of generations which have dedicated themselves to growing maize, primary source of income, etc.).

Table 1 shows a series of descriptive statistics, at a provincial level, on the growing of flint maize. As can be seen, 98% of the land being dedicated to flint maize farming is to be found in these four provinces; primarily in the provinces of Los Ríos (45%) and Manabí (25%). The average size of a producer's farm is quite small, ranging from 4.8 ha in Manabí to 6.7 ha in Los Ríos. Furthermore, hybrid maize was found to be widespread in the provinces studied. The province with the lowest percentage of farmers using hybrid seed is Manabí (65%); while the province with the highest spread is Los Ríos, where 76% of producers use it. Nevertheless, the spread of irrigation systems in these places is less. For example, in Los Ríos only 10% of maize producers use an irrigation system, while Lojas has the highest registered number (27%). There are also some provincial differences in terms of the percentage of producers who belong to a farming association, this ranges between 24% in Lojas to 43% in the case of Los Ríos.

Table 1. Descriptive production statistics for maize at a provincial level

Province	Area of land where maize is harvested compared to the rest of the country (%)	Size of farm (average hectares)	Area sown with maize (average hectares)	Producers who use hybrid seeds (%)	Producers with an irrigation system (%)	Producers who belong to an association (%)
Los Ríos	45	6.7	4.9	76	10	43
Manabí	25	4.8	3.9	65	18	28
Guayas	16	5.5	2.6	69	27	34
Loja	12	6.5	3.1	70	31	24

Source: GCSIN survey carried out in 2015 and 2016 (MAG, 2018).

The result variable (RV) which we expect to use to estimate the impact of hybrid seed is the productivity of the land expressed in terms per hectare and, according to Castro (2016), is calculated according to the following formula:

$$RV = \frac{pc * (100 - humidity\ percentage - impurity\ percentage)}{100 - (fixed\ humidyt\ percentage - fixed\ impurity\ percentage)}$$

Where:

$$pc = \frac{ears\ per\ hectare * ears'average\ weight\ (grams)}{1000000\ (grams/metric\ tons)}$$

PC:[4] calculates the *field weight* or crop yield. It is a "raw" datum which is adjusted in accordance with humidity and impurities, in order to obtain productivity (in tons per hectare).

fixed humidity percentage: 13

fixed impurity percentage: 1

ears of maize per hectare: using the length of the furrow and number of ears per ten meters.

average weight of ears: average weight of the ears acquired

percentage of humidity and impurities: data acquired from the sampling laboratory.

To evaluate the effect of hybrid seed adopted independently by farmers, the *SEED* treatment variable was created, which is dichotomous and has a value of 1 for producers who adopted the hybrid seed but acquired it on their own and 0 for those who did not use a hybrid seed. Meanwhile there is the treatment variable which operationalizes the adoption of the hybrid seed by way of the technological package, called KIT, which is also dichotomous and has a value of 1 for producers who adopt the hybrid seed through the technological package seed kit and 0 for individuals who do not use hybrid seed. Here it is important to clarify that flint maize producers who do not use the commercial hybrid seed use recycled seeds from other hybrids and traditional seeds. Some farmers in their desire to reduce the cost of the commercial hybrid seed use seeds recycled from past crops or get it from their neighbors. These seeds are considered to be 20% less productive, with around 40% germinating power and are much more susceptible to infestations and diseases (Zambrano, 2016). While the traditional seed is used to a greater degree in the province of Manabí, the best known traditional materials are called "Salprieta", "Criollo" and seeds from the breed "Tusilla" (Yánez, 2014).

In Table 2 we see the number of producers treated or not treated, for each treatment, as well as their average productivity per hectare. As one can see, the majority of farmers use hybrid seeds (1436 to 163) and of those the majority acquired it on their own (981 to 455). Finally, one can see that on average producers who use hybrid seeds are more productive per hectare and that those who adopt it by means of a technical technological package are those who display a greater level of productivity per hectare.

Table 2. Descriptive statistics on land productivity according to the designed treatment variables

Treatment	*Description*	*Treated*	*Not treated*	*Average and standard deviation of RV*	
				Treated	*Not treated*
KIT	Farmers who adopted the seed via the seed kit	455	163	5.88 (1.63)	4.78 (1.76)
SEMILLA	Farmers who adopted the seed independently	981	163	5.65 (1.86)	4.78 (1.76)

Notes: standard deviation in parentheses; *RV*=result variable.

Source: created by the authors.

Methodology

If $T \in [0,1]$ is one of the treatment variables defined previously (KIT or SEED) and $Y \in [0,1]$ the *RV*; the average treatment effect on the treated (ATT) can be calculated in the following manner:

$$ATT = E(Y_{1i}|T = 1) - E(Y_{0i}|T = 1) \quad (1)$$

Where Y_{1i} is the productivity per hectare for producer *i* when he receives the treatment and Y_{0i} is productivity per hectare for the same producer *i* if he did not receive the treatment. In equation (1) one can see the methodological problem faced at the moment of estimating the impact of the hybrid seed, as $E(Y_{0i}|T = 1)$ is a result which cannot be observed in the database. As such, with the available information, the causal effect can only be estimated for the difference in averages between the treated individuals and those who are not treated, which is formally expressed in the following manner:

$$E(Y_{1i}|T = 1) - E(Y_{0i}|\mathrm{T} = 0)) \quad (2)$$

Note that equation (2) would allow estimating the causal effect if the treatment assignation were random; given that in this case it would happen that $E(Y_{0i}|T = 1) = E(Y_{0i}|T = 0))$. This last part would allow one to confirm that *T* is independent of potential results, that is: $T \perp (Y_{0i}, Y_{1i})$. Nevertheless, given that the assignation of treatment is not random, rather it is the producers who decide to adopt the seed, it is possible that their own differentiating characteristics, which influenced the adoption of the treatment, could also influence the *RV*. Therefore, with the aim of estimating the real causal effect, this research used propensity score matching (PSM) (Rosenbaum and Rubin, 1985). PSM eliminates the selection bias by creating a counterfactual one by means of pairing the treated individuals with those who are not treated based on the probability of receiving treatment (Rosenbaum and Rubin, 1985). That way the treated individuals are compared with those who were not treated but have the same probability of receiving treatment.

As such, the first methodological step starts with the estimation of each individual's (treated or not treated) probability of receiving treatment based on a series of observable characteristics, which is known as the propensity score. Once the appropriate propensity scores are estimated, in order to estimate the effect of treatment, treated individuals are compared with those who are not treated but have a similar propensity score. Within the matching strategies, a treated individual can be matched with a control individual with the closest propensity score or they can be matched with various individuals in the control group. In this regard the nearest neighbor matching algorithm (NNM) consists of matching each treated individual with the untreated one with the closest propensity score (Rodríguez, 2012; Caliendo and Kopeinig, 2005), in order to later calculate the differences of their averages resulting from their variables (Beck and Ichino, 2002). For its part, Kernel Based Matching (KBM) calculates the counterfactual using the weighted averages of the individuals in the control group and assigns greater weight to the observations which are closer in regards to their propensity score. This method compares the result variables of the treated and untreated, assigning greater weight to the latter according to just how similar their propensity scores are (Handouyahia *et al*., 2013). As such, this estimator provides some advantages in regards to a lower variance, as it uses more information than others (Guerzoni and Raiteri, 2015; Caliendo and Kopeinig, 2005).

The validity of this method is based on fulfilling two assumptions which we will now describe.

Average conditional independence: the potential result is independent, conditioned on the probability of receiving treatment, which is described as such:

$$T \perp (Y_{0i}, Y_{1i}) | p(x))$$

Where *p(x)* is the ability of receiving treatment, conditioned on a set of covariables *x* or propensity score.

Common support: each individual has the possibility of being treated or not being treated given the covariables, this is expressed in the following manner:

$$0 < p(T = 1 | X = x) < 1$$

Given the assumption of average conditional independence, in calculating propensity scores, it behooves us to include all covariables related with *RV* and with the probability of receiving treatment (Rosenbaum and Rubin, 1985) (see Table 3).

Table 3. Description of variables for calculating propensity score

Name	*Description*	*KIT*	*SEED*	*Control*
Farm size	Natural logarithm for number of hectares	1.56 (0.79)	1.36 (0.94)	0.88 (0.86)
Type of crop	Dichotomous variable which takes on the value of 1 for a singular crop of maize and 0 if otherwise	0.97 (0.18)	0.96 (0.19)	0.94 (0.24)
Mechanized planting	Dichotomous variable which takes on the value of 1 if the producer has mechanized planting and 0 if otherwise	0.27 (0.45)	0.25 (0.43)	0.21 (0.41)
Mechanized harvest	Dichotomous variable which takes on the value of 1 if the producer has mechanized harvesting and 0 if otherwise	0.30 (0.46)	0.24 (0.43)	0.16 (0.37)
Belongs to an association	Dichotomous variable which takes on a value of 1 if the producer belongs to a farming association and 0 if otherwise	0.57 (0.50)	0.28 (0.45)	0.22 (0.42)
Urban parish	Dichotomous variable which takes on a value of 1 if the producer belongs to an urban parish and 0 if otherwise	0.64 (0.48)	0.64 (0.48)	0.58 (0.50)
Farmer's age	Natural logarithm of the farmer's age	3.81 (0.30)	3.81 (0.32)	3.89 (0.35)
First generation	Dichotomous variable which takes on a value of 1 if the producer represents the first generation dedicated to maize and 0 if otherwise	0.13 (0.34)	0.19 (0.40)	0.31 (0.46)
Second generation	Dichotomous variable which takes on a value of 1 if the producer represents the second generation dedicated to maize and 0 if otherwise	0.48 (0.50)	0.40 (0.49)	0.34 (0.47)
Further generations	Dichotomous variable which takes on the value of 1 if the producer comes from a line of more than two generations dedicated to maize and 0 if otherwise	0.39 (0.49)	0.41 (0.49)	0.36 (0.48)
Source of income	Dichotomous variable which takes on the value of 1 if maize represents the primary source of income for the producer and 0 if otherwise	0.86 (0.35)	0.81 (0.39)	0.67 (0.47)
Year2015_Winter	Dichotomous variable which takes on a value of 1 if the producer planted in the winter of 2015 and 0 if otherwise	0.47 (0.50)	0.15 (0.36)	0.26 (0.44)
Year2015_Summer	Dichotomous variable which takes on a value of 1 if the producer planted in the summer of 2015 and 0 if otherwise	0.33 (0.47)	0.23 (0.42)	0.19 (0.39)
Year2016_Winter	Dichotomous variable which takes on a value of 1 if the producer planted in the winter of 2016 and 0 if otherwise	0.15 (0.35)	0.34 (0.47)	0.32 (0.47)
Year2016_Summer	Dichotomous variable which takes on a value of 1 if the producer planted in the summer of 2016 and 0 if otherwise	0.05 (0.22)	0.27 (0.45)	0.23 (0.42)

Note: average and standard deviation between parentheses.

Source: created by the authors.

In Table 4 we have the results of the estimations of the propensity score models for each of the treatments, which given their dichotomous nature are estimated by logit models.

Table 4. Estimation of the propensity score for KIT and SEED treatments

	KIT		*SEED*	
	Coefficient	*Standard error*	*Coefficient*	*Standard error*
Farm size	0.422 ***	0.08	0.338 ***	0.058
Type of crop	0.302	0.307	0.302	0.225
Mechanized planting	-0.151	0.166	-0.087	0.123
Mechanized harvest	0.278	0.163	0.338 **	0.130
Belongs to an association	0.874 ***	0.145	-0.006	0.118
Urban parish	0.110	0.135	0.001	0.103
Farmer's age	-0.687 ***	0.205	-0.496 ***	0.152
Second generation	0.595 ***	0.174	0.359 ***	0.126
Further generations	0.468 **	0.179	0.427 ***	0.129
Source of income	0.488 ***	0.153	0.367 ***	0.111
Environmental factors				
Year2015_Winter	1.145 ***	0.224	--	--
Year2015_Summer	1.054 ***	0.225	0.512 ***	0.153
Year2016_Winter	0.623 **	0.242	0.446 ***	0.140
Year2016_Summer	--	--	0.525 ***	0.154
Pseudo R2	0.290		0.100	
Wald chi2	128.080		84.900	

Notes: *p<0,05; ** p<0,01; *** p<0,001; The variable "Urban parish" in Ecuador is understood in a territorial organizational context as "parishes" there are similar in nature to municipalities; The variable "first generation" was excluded from the table as it constitutes a reference category for the other generational variables;– said variables constitute the reference category.

Source: created by the authors.

The results of Table 4 show that independently of the adoption method, producers who have a larger farm are younger, come from a longer line of maize farmers and those whose primary source of income is maize were more likely to adopt hybrid maize. These results agree with that found in other empirical studies on the determinants of adopting farming technologies (Uaiene *et al*., 2009; Foster and Rosenzweig, 2014; Mason and Smale; 2013; Ali and Abdulai, 2010; Awotide *et al*., 2016).

On the other hand, the results indicated producers who belong to a farming association were more likely to adopt a new seed by means of a technological package and that belonging to an association is not related with them adopting it on their own. In this regard, there is evidence that indicates that belonging to an association facilitates the adoption of new farming technologies (Ali and Abdulai, 2010; Uaiene *et al*., 2009; Tiamiyu *et al*., 2009), given that the association members interact with each other, allowing them to exchange technological information.

Finally, farmers with mechanized harvesting were more likely to acquire a seed independently; while this is not associated with the probability of adoption by means of the seed kit.

Before it is possible to estimate the effect of each treatment it is necessary to verify whether they meet the two assumptions on which the method is based. The assumption of conditional independence requires that after matching, treated and untreated individuals be equal in the covariables included in calculating the propensity score and which were defined in Table 3. As such, Tables 5 and 6 show the results of the differences test for the covariables' averages between those treated and not treated before and after matching, in both NNM and KBM. Table 5 does so for the KIT treatment while Table 6 does so for the SEED treatment.

Table 5. Balance of covariables after applying matching algorithms (NNM and KVM) in KIT treatment

	Before matching			*NNM*			*KBM*		
	Control	*Treated*		*Control*	*Treated*		*Control*	*Treated*	
Farm size	0.875	1.560	***	1.595	1.530	NS	1.549	1.530	NS
Type of crop	0.938	0.967	NS	0.986	0.966	NS	0.985	0.966	NS
Mechanized planting	0.214	0.274	NS	0.347	0.275	**	0.332	0.275	NS
Mechanized harvest	0.159	0.303	***	0.207	0.286	**	0.302	0.286	NS
Belongs to an association	0.221	0.567	***	0.580	0.555	NS	0.525	0.555	NS
Urban parish	0.576	0.639	NS	0.573	0.636	NS	0.560	0.636	*
Farmer's age	3.891	3.805	***	3.786	3.810	NS	3.800	3.810	NS
First generation	0.306	0.131	***	0.155	0.135	NS	0.116	0.135	NS
Second generation	0.337	0.476	**	0.395	0.471	**	0.425	0.471	NS
Further generations	0.355	0.391	NS	0.449	0.392	NS	0.458	0.392	NS
Source of income	0.668	0.857	***	0.830	0.853	NS	0.823	0.853	NS
Environmental Factors									
Year2015_Winter	0.263	0.474	***	0.435	0.460	NS	0.478	0.460	NS
Year2015_Summer	0.190	0.327	***	0.383	0.336	NS	0.339	0.336	NS
Year2016_Winter	0.319	0.147	***	0.117	0.151	NS	0.122	0.151	NS
Year2016_Summer	0.226	0.050	***	0.063	0.051	NS	0.059	0.051	NS
Bias range (%)	7 – 83.2			0.22-19			0.28 – 15.7		

KBM = Kernel based matching; NNM=nearest neighbor matching; NS=not significant; * p<0,05; ** p<0,01; *** p<0,001.
Source: created by the authors.

Table 6. Balance of covariables after applying the matching algorithms (NNM and KBM) in the SEED treatment.

	Before matching			*NNM*			*KBM*		
	Control	*Treated*		*Control*	*Treated*		*Control*	*Treated*	
Farm size	0.875	1.360	***	1.285	1.325	NS	1.247	1.325	NS
Type of crop	0.938	0.964	NS	0.982	0.966	**	0.960	0.966	NS
Mechanized planting	0.214	0.252	NS	0.235	0.248	NS	0.217	0.248	NS
Mechanized harvest	0.159	0.238	**	0.262	0.228	NS	0.252	0.228	NS
Belongs to an association	0.220	0.282	NS	0.277	0.282	NS	0.268	0.282	NS
Urban parish	0.576	0.637	NS	0.631	0.634	NS	0.609	0.634	NS
Farmer's age	3.891	3.806	***	3.820	3.812	NS	3.820	3.812	NS
First generation	0.306	0.194	***	0.194	0.197	NS	0.193	0.197	NS
Second generation	0.337	0.399	NS	0.400	0.392	NS	0.406	0.392	NS
Further generations	0.355	0.405	NS	0.404	0.409	NS	0.400	0.409	NS
Source of income	0.668	0.807	***	0.92	0.804	NS	0.810	0.804	NS
Environmental factors									
Year2015_Winter	0.263	0.152	***	0.138	0.152	NS	0.186	0.152	*
Year2015_Summer	0.190	0.233	NS	0.224	0.232	NS	0.229	0.232	NS
Year2016_Winter	0.319	0.339	NS	0.380	0.343	NS	0.342	0.343	NS
Year2016_Summer	0.226	0.274	NS	0.255	0.271	NS	0.241	0.271	NS
Bias range (%)	4.3 – 53.8			0.2 – 8.4			0.2 – 8.6		

KBM= Kernel based matching; NNM=nearest neighbor matching; NS=not significant; * $p<0,05$; ** $p<0,01$; *** $p<0,001$.

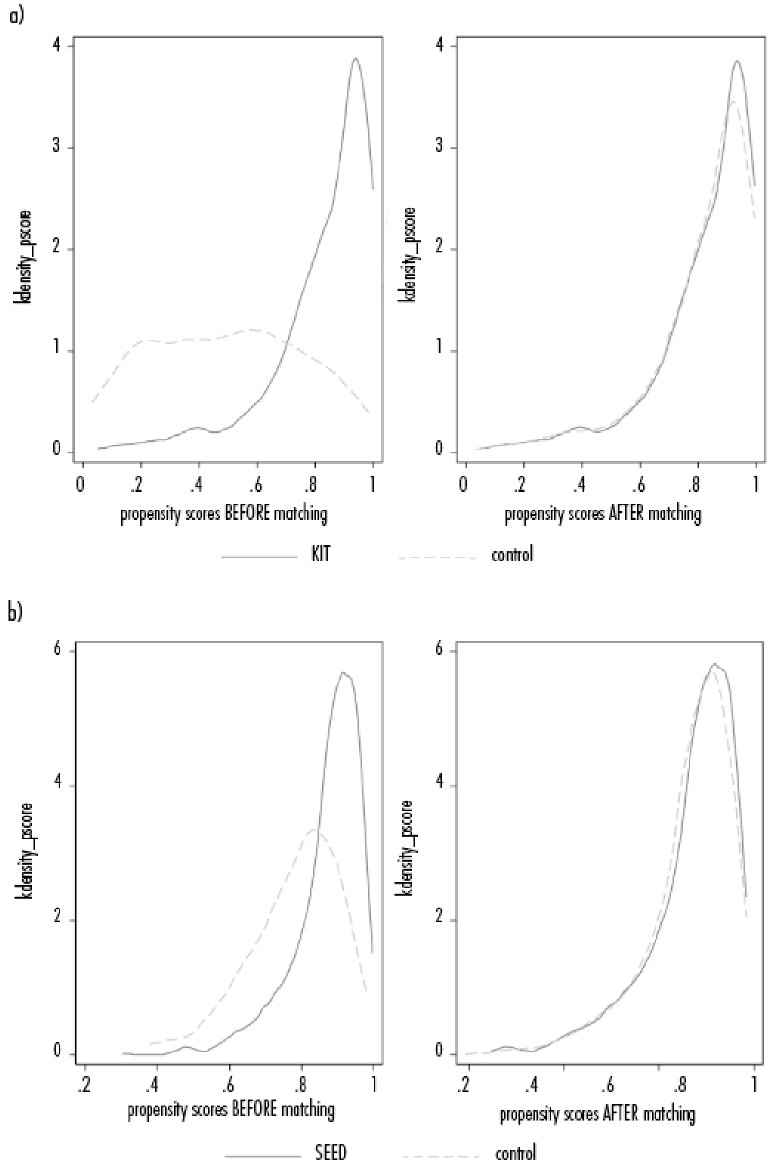
Source: created by the authors.

The results of Table 5 indicate that prior to matching, the farmers who adopted seeds by means of the kit were different to those who did not in terms of farm size, mechanized harvest, belonging to an association, age and number of generations dedicated to maize farming. Nevertheless, after matching, the differences in averages are reduced, primarily with the KBM algorithm which only shows one significant difference; 90% when it comes to the variable of belonging to an urban parish. As a result, this algorithm offers more trustworthy results. For its part, Table 6 also reveals significant differences prior to matching; after matching, both algorithms take on a balance between covariables.

Finally, the assumption of common support requires the existence of units, both in the control group and among those who were treated, with the same propensity scores. As such there should be an overlap in the propensity score distribution among both groups. Nevertheless, there will be cases of units which do not have the same probability of receiving treatment. This implies that the estimation of the effect is carried out in the area of common support (Rodríguez, 2012).

Figure 1 shows the density of the propensity values for each one of the treatments before and after KBM.[5] As one can see, the differences are corrected after the process. The figures show that lining up the propensity scores reduces the dissimilarities in distributions. The high degree of overlap indicates the high quality of the matching procedure.

Figure 1. Overlap evaluation (KBM algorithm): a) KIT treatment and B) SEED treatment



Note: KBM=Kernel based matching.
Source: created by the authors.

Please note that meeting the assumption of common support causes the exclusion of individuals which do not have any overlap. When the proportion of individuals who were excluded from the analysis is small one can expect few complications (Becerril and Abdulai, 2010). In the current study, not meeting the requirement of common support created few losses in the observations: 2.6% for the KIT treatment and 2% for the SEED treatment (see Table 7). As such, one can dismiss these losses of information when reading the results.

Table 7. Number of individuals per treatment in the study, along with the losses due to common support

Treatment	*Number of treated individuals*	*Number of individuals not treated*	*Losses in meeting the assumption of common support*
KIT	443	163	12 (2.6%)
SEED	961	163	20 (2.0%)

Source: created by the authors.

4. RESULTS

Table 8 shows the average effect of KIT and SEED treatments on productivity per hectare, both for KBM as well as NNM. As one can see, the estimated ATT in both algorithms is quite similar, which strengthens the results.

Table 8. ATT by KIT and SEED treatments.

Algorithm	Treatment	Treated	Control	ATT		Standard Error	"t" Statistic
KBM	KIT	1.734	1.461	0.272	***	0.067	4.07
	SEED	1.671	1.549	0.122	**	0.042	2.88
NNM	KIT	1.734	1.485	0.244	***	0.08	3.06
	SEED	1.671	1.567	0.105	*	0.054	1.94

KBM= kernel based matching; NNM=nearest neighbor matching. * p<0,05; ** p<0,01; *** p<0,001.
Source: created by the authors.

The results of Table 8 indicate that both producers who acquired hybrid seeds by means of a seed kit, as well as those who did so independently, present a greater productivity per hectare than producers who did not acquire the new seed variety, regardless of which matching algorithm is selected. Furthermore, the results from the Kernel algorithm show that the ATT obtained for the KIT treatment and for the SEED treatment were 0.272 and 0.122 respectively; this indicates that producers who adopted the seed along with complementary technology and training from the seed kit got higher gains in productivity per hectare than those who adopted it on their own.

In the first place, the results line up with the majority of empirical evidence which indicates positive effects on productivity for adopters of hybrid maize seeds (Besley and Case, 1993; Doss and Morris, 2001; Mendola, 2007; Becerril and Abdulai, 2010; Kutka, 2011; Olaniyan and Lucas, 2004; Lunduka *et al*., 2012; Khonje *et al*., 2015; Karim *et al*., 2010; Setimela *et al*., 2017; Bellon and Hellin, 2011; Akhter *et al*., 2020). Nevertheless, they suggest that the seed's performance is greater when accompanied by complementary technology and training. This is because producers who acquired the seeds through technological packages have a greater productivity per hectare than those who acquired it independently. As such, these results line up with the empirical literature which states that producers who adopt new technologies and at the same time acquire complementary assets and technical production knowledge by means of training, tend to generate greater productivity gains than those who do not (Grander, 2003; Bartel *et al*., 2007; Boothby *et al*., 2010).

The results show the importance of spreading hybrid maize in Ecuador. Without a doubt, the differences in yield per hectare of hybrid maize versus traditional maize explain the spread of hybrid maize in the four provinces studied. Additionally, the results justify the suitability of complementing subsidies for new seed varieties with complementary training and technologies so that producers can get greater yields from farming innovations.

5. CONCLUSIONS

The current study analyzes the impact of adopting hybrid maize on productivity per hectare for producers in the four flint maize producing provinces in Ecuador for the years 2015 and 2016. Furthermore, we examine whether the impact of seed adoption differs between producers who acquired it independently or those who adopted it by means of a technological package which, in addition to the seed included a series of complementary technologies such as fertilizers, rooting agents, pesticides and training on the use of the seed. For estimating the effects of adopting the hybrid seed, be it independently or by means of a technological package, we used the propensity score matching methodology by means of the nearest neighbor matching and Kernel based matching algorithms.

The results indicate that the producers who adopt hybrid seeds, whether independently or by seed packages, demonstrate a greater productivity per hectare than those who use traditional seed. On the other hand, we noted a greater effect from the seed when it was adopted by means of a technological package. Based on these results, one can argue that the performance a farmer can get by using a new seed depends on whether they have or can acquire the technologies, training, and skills that are required for the efficient use of the new seed. This lines up with the extensive literature which points out that companies which adopt new technologies and at the same time acquire complementary techno-productive assets and knowledge, see greater gains in productivity than those who do not (Grander, 2003; Bartel *et al*., 2007; Boothby *et al*., 2010).

The results acquired have clear implications for policy implementation for the spread of farming technologies in developing and emerging countries. Policies which facilitate the acquisition of new farming technologies by means of subsidies and which offer complementary technology and training, can influence producers not only to adopt new technologies but also to make efficient use of said technologies, thereby improving their productivity levels. This implies the need for coordinating policies which provide incentives for adopting technologies with those who provide training, education and technical support. As such, the increase in farming productivity requires governments to implement a wide range of measures which go from incentivizing technological adoption, financing universities and research centers for agricultural innovation and providing various types of training. As such, it is a pressing matter to strengthen the policies and institutions of these countries so that new technologies spread faster and producers attain greater yields in these areas.

A final point is that at the time of evaluating the effects of adopting hybrid maize, it is relevant to analyze its impact on other measures of the farmer's well-being. Analyzing the impact only in terms of productivity per hectare could hide how hybrid maize adoption could affect other aspects. As such, it is important to extend the study to other result variables and then evaluate whether the adoption of new seeds also guarantees different impacts on other aspects which are relevant to farmers.

BIBLIOGRAPHY

Abate, G., Shahidur T., Borzaga, C. and Getnet, K. (2016), “Rural finance and agricultural technology adoption in Ethiopia: Does the institutional design of lending organizations matter?”, *World Development*, vol. 84, DOI <https://doi.org/10.1016/j.worlddev.2016.03.003>

Adesina, A. and Zinnah, M. (1993), “Technology characteristics, farmers’ perceptions and adoption decisions: A Tobit model analysis in Sierra Leone”, *Agricultural Economics,* vol. 9, no. 4, December, DOI <https://doi. org/10.1016/0169-5150(93)90019-9>

Akhter, A., AbduRahman, B. I. and Dil, A. R. (2020), “Adoption and impact of the maize hybrid on livelihood of the maize growers: Some policy insights from Pakistan”, *Scientifica*, vol. 2020, DOI <https://doi. org/10.1155/2020/5959868>

Ali, A. and Abdulai, A. (2010), “The adoption of genetically modified cotton and poverty reduction in Pakistan”, *Journal of Agricultural Economics,* vol. 61, no. 1, DOI <https://doi.org/10.1111/j.1477-9552.2009.00227.x>

Awotide, A., Karimov, A. and Diagne, A. (2016), “Agricultural technology adoption, commercialization and smallholder rice farmer’s welfare in rural Nigeria”, *Agricultural and Food Economics,* vol. 4, no. 3, DOI <https://doi. org/10.1186/s40100-016-0047-8>

Bartel, A., Ichniowski, C. and Shaw, K. (2007),“How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement and worker skills”, *The Quarterly Journal of Economics,* vol. 122, no. 4, Oxford University Press. Available at <www. jstor.org/stable/25098887>

Becerril, J. and Abdulai, A. (2010), “The impact of improved maize varieties on poverty in Mexico: A propensity score-matching approach”, *World Development,* vol. 38, no. 7, DOI <https://doi.org/10.1016/j. worlddev.2009.11.017>

Becker, S. and Ichino, A. (2002), “Estimation of average treatment effects based on propensity scores”, *Stata Journal,* vol. 2, no. 4, DOI <https://doi. org/10.1177/1536867X0200200403>

Bellon, M. R. and Hellin, J. (2011), “Planting hybrids, keeping landraces: agricultural modernization and tradition among small scale maize farmers in Chiapas, Mexico”, *World Development*, vol. 8, no. 39, DOI <https://doi. org/10.1016/j.worlddev.2010.12.010>

Besley, T. and Case, A. (1993), “Modeling technology adoption in developing countries”, *The American Economic Review*, vol. 83, no. 2, American Economic Association. Available at <www.jstor.org/stable/2117697>

Boothby, D., Dufour, A. and Tang, J. (2010), “Technology adoption, training and productivity performance”, *Research Policy,* vol. 39, no. 5, DOI <https://doi.org/10.1016/j.respol.2010.02.011>

Caliendo, M. and Kopeinig, S. (2005), “Some practical guidance for the implementation of propensity score matching”, *Journal of Economic Surveys*, vol. 22, no. 1, DOI <https://doi.org/10.1111/j.1467-6419.2007.00527.x>

Carrillo, G. (2014), *Desarrollo rural y cooperativismo agrario en Ecuador: trayectorias históricas de los pequeños productores en la economía global,* Madrid, Ministerio de Agricultura, Alimentación y Medio Ambiente. Available at <http://hdl.handle.net/10201/45840>

Doss, C. R. and Morris, M. L. (2001), “How does gender affect the adoption of agricultural innovations? The case of improved maize technology in Ghana”, *Agricultural Policy*, vol. 25, DOI <https://doi.org/10.1016/S0169- 5150(00)00096-7>

Castro, M. (2016), *Rendimientos de maíz duro seco en invierno 2016* (Working Document), Quito, Dirección de Análisis y Procesamiento de la Información. Coordinación General del Sistema de Información Nacional del Ministerio de Agricultura, Ganadería, Acuacultura y Pesca.

Feder, G. and Umali, D. (1993), “The adoption of agricultural innovations a review”, *Technological Forecasting and Social Change,* vol. 43, no. 3-4, DOI <https://doi.org/10.1016/0040-1625(93)90053-A>

Foster, A. D. and Rosenzweig, M. R. (1996), “Technical change and human- capital returns and investments: Evidence from the Green Revolution”, *The American Economic Review*, vol. 86, no. 4, American Economic Association. Available at <https://www.jstor.org/stable/2118312>

______ and Rosenzweig, M. (2014), “Microeconomics of technology adoption”, *Annual Review of Economics,* vol. 2, DOI <https://doi.org/10.1146/ annurev.economics.102308.124433>

Grander, J. P. (2003), “Technology adoption and labour training under uncertainty”, *Economics of Education Review*, vol. 22, DOI <https://doi. org/10.1016/S0272-7757(02)00035-3>

Guerzoni, M. and Raiteri, E. (2015), “Demand-side *vs*. supply-side technology policies: Hidden treatment and new empirical evidence on the policy mix”, *Research Policy,* vol. 44, DOI <https://doi.org/10.1016/j.res- pol.2014.10.009>

Handouyahia, A., Haddad, T. and Eaton, F. (2013), “Kernel matching *versus* inverse probability weighting: A comparative study”, *International Journal of Mathematical, Computational, Physical, Electrical and Computer Engineering,* vol. 7, no. 8, France, World Academy of Science, Engineering and Technology. Available at <https://panel.waset.org/publications/16101/ pdf>

Karim, M. R., Moniruzzaman, M. and Alam, Q. M. (2010), “Economics of hybrid maize production in some selected areas of Bangladesh”, *Bangladesh Journal of Agricultural Research,* vol. 35, no. 1, DOI < https://doi. org/10.3329/bjar.v35i1.5869>

Khonje, M., Manda, A., Arega, A. and Kassei, M. (2015), “Analysis of adoption and impacts of improved maize varieties in eastern Zambia”, *World Development*, vol. 66, DOI <https://doi.org/10.1016/j.worlddev.2014.09.008>

Kohli, D. and Singh, N. (1997), *The Green Revolution in Punjab, India: The economics of technical change*, Technical report, Conference on Agriculture of the Punjab at the Southern Asian Institute, Columbia University.

Kutka, F. (2011), “Open-pollinated *vs*. hybrid maize cultivars”, *Sustainability*, vol. 3, no. 4, DOI <10.3390/su3091531>

Lacki, P. (2011), *El libro de los pobres rurales. Desarrollo agropecuario: de la independencia al protagonismo del agricultor,* Curitiva, RazonEs de SER.

Lunduka, R., Fisher, M. and Snapp, S. (2012), “Could farmer interest in a diversity of seed attributes explain adoption plateaus for modern maize varieties in Malawi?”, *Food Policy*, vol. 37, no. 5, DOI <https://doi.org/10.1016/j. foodpol.2012.05.001>

Mason, N. and Smale, M. (2013), “Impacts of subsidized hybrid seed on indicators of economic well-being among smallholder maize growers in Zambia”, *Agricultural Economics,* vol. 44, no. 6, DOI <https://doi.org/10.1111/ agec.12080>

Mauceri, M., Alwang, J., Norton, G. and Barrera, V. (2007), “Effectiveness of integrated pest management dissemination techniques: a case study of potato farmers in Carchi, Ecuador”, *Journal of Agricultural and Applied Economics,* vol. 39, no. 3, DOI <https://doi.org/10.1017/S10740708 00023403>

Mendola, M. (2007), “Agricultural technology adoption and poverty reduction: A propensity score analysis for rural Bangladesh”, *Food Policy*, vol. 32, DOI <https://doi.org/10.1016/j.foodpol.2006.07.003>

Mignouna, B., Manyong, M., Rusike, J., Mutabazi, S. and Sekondo, M. (2011), “Determinants of adopting imazapyr resistant maize techology and its impact on household income in western Kenya”, *AgBioforum,* vol. 14, no. 3, University of Missouri-Columbia. Available at <http://agbioforum. org/v14n3/v14n3a07-mignouna.htm>

Ministerio de Agricultura y Ganadería (MAG) (2018), Encuesta de la Coordinación General del Sistema de Información Nacional de los años 2015 y 2016. Recovered from <https://bit.ly/2wQgFR3>

Mwangi, M. and Kariuki, S. (2015), “Factors determining adoption of new agricultural technology by smallholder farmers in developing countries”, *Journal of Economics and Sustainable Development*, vol. 6, no. 5, 6, International Institute for Science, Technology & Education. Available at <https://www.iiste.org/Journals/index.php/JEDS/article/view/20710>

Nadal, A. and Wise, T. (2019), *Los costos ambientales de la liberalización agrícola: el comercio de maíz entre México y EE.UU. en el marco del NAFTA*, Globalización y medio ambiente: Lecciones desde las Américas (Grupo de Trabajo sobre Desarrollo y Medio Ambiente en las Américas), Heinrich Boll Foundation.

Nazziwa-Nviiri, L., Van Campenhout, B. and Amwonya, D. (2017), *Stimulating agricultural technology adoption lessons from fertilizer use among Ugandan potato farmers* (Discussion Paper 01608), International Food Policy Research Institute.

Olaniyan, A. B. and Lucas, E. O. (2004), “Maize hybrids cultivation in Nigeria- a review”, *Journal of Food, Agriculture and Environment*, vol. 2, no. 3 and 4 DOI <https://doi.org/10.1234/4.2004.278>

Ouadahi, J. (2008), “A qualitative analysis of factors associated with user acceptance and rejection of a new workplace information system in the public sector: a conceptual model”, *Canadian Journal of Administrative Sciences*, vol. 25, DOI <https://doi.org/10.1002/cjas.65>

Pan, D. (2014), “The impact of agricultural extension on farmer nutrient management behavior in Chinese rice production: A household-level analysis”, *Sustainability,* vol. 10, no. 6, DOI <https://doi.org/10.3390/su6106644>

Rodríguez, M. (2012), *Técnicas de Evaluación de Impacto: Propensity Score Matching y Aplicaciones Prácticas con Stata* (Document No. 2), Spain, Instituto de Estudios Fiscales.

Rogers, E. (1971), *Diffusion of innovations*, 3rd edition, New York, Free Press.

Rosenbaum, P. and Rubin, D. (1985), “Constructing a control group using multivariate matched sampling methods that incorporate the propensity score”, *The American Statistician*, vol. 39, no. 1, DOI <10.2307/2683903>

Runge, C. F. (2002), *US agricultural policy in 2002: A four dimensional disaster*, Winnipeg, George Morris Centre. Ruttan, V. W. (1996), “What happened to technology adoption diffusion research”, *Sociologia Ruralis,* vol. 36, no. 1, DOI https://doi. org/10.1111/j.1467-9523.1996.tb00004.x

Saín, G. and Martínez, J. (1999), *Adoption and use of improved maize by small-scale farmers in southeast Guatemala,* CIMMYT Economics Paper 99-04, Mexico, CIMMYT.

Selis, D. (2000), “Efectos del cambio tecnológico sobre las condiciones de producción y reproducción del sector hortícola de La Plata”, in R. Ringuelet, *Espacio tecnológico, población y reproducción social en el sector hortícola de La Plata,* La Plata, UNLP, FAHCE.

Setimela, P. S., Magorokosho, C., Lunduka, R., Gasura, E., Makumbi, D., Tarekegne, A., Cairns, J. E., Ndhlela, T., Erenstein, O. and Mwangi, W. (2017), “On-farm yield gains with stress-tolerant maize in eastern and Southern Africa”, *Agronomy Journal*, vol. 2, no. 109, DOI <http://dx.doi. org/10.2134/agronj2015.0540>

Shively, G. and Ricker-Gilbert, J. (2013), *Measuring the impact of agricultural in- put subsidies in sub-Saharan Africa: Evidence from Malawi’s farm input subsidy program*, Pardue Policy Research Institute (PPRI) Policy Briefs, vol. 1. Available at <https://docs.lib.purdue.edu/gpripb/vol1/iss1/4>

Sistema de Información Pública Agropecuaria (SIPA) (2020), *Ficha de cultivo de maíz duro seco*. Recuperado de <http://sipa.agricultura.gob.ec/index. php/maiz>

Teece, D. (1986), “Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy”, *Research Policy,* vol. 15, no. 6, DOI <https://doi.org/10.1016/0048-7333(86)90027-2>

______ (1988), *Pro ting from technological innovation: Implications for integration, collaboration, licensing and public policy*, London, Printer.

Tiamiyu, S. A., Akintola, J. O. and Rahji, M. A. Y. (2009), “Technology adoption and productivity difference among growers of new rice for Africa in Savanna Zone of Nigeria”, *Tropicultura,* vol. 27, no. 4, Belgium, Agri- Overseas. Available at <http://www.tropicultura.org/text/v27n4/193. pdf>

Todaro, M. and Smith, S. (2012), *Economic Development*, Boston, Addison- Wesley.

Uaiene, R., Arndt, C. and Masters, W. (2009), *Determinants of agricultural technology adoption in Mozambique* (Discussion papers No. 67E), Mozambique, National Directorate of Studies and Policy Analysis y Ministry of Planning and Development.

Yánez, C. (2014), *Programa de Maíz* (Informe Anual), Quito, Estación Experimental Santa Catalina del Instituto Nacional de Investigaciones Agropecuarias.

Zambrano, J. (July 2016), “INIAP, mantiene en vigencia cuatro híbridos para el cultivo de maíz”, *Revista Técnica Maíz & Soya*. Recovered from <https://issuu.com/maizysoya/docs/mys_julio_web>

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[1] TL note: Ministry of Agriculture and Livestock, from the original Spanish *Ministerio de Agricultura y Ganado*.

[2] TL note: From the original Spanish *Coordinación General del Sistema de Información Nacional*.

[3] Los Ríos (56m of above sea level, 25.3°C temperature, 2060mm of rainfall), Manabí (18m, 25.7°C, 699mm). Guayas (120m, 23.7°C, 1181mm). Loja (200m, 24.9°C, 398mm) data acquired from clima–data.org

[4] From the Spanish *peso de campo*

[5] The figure corresponding to the NNM algorithm is available upon request from the lead author.