Technology Awareness and Adoption: The Case of Improved Pigeonpea Varieties in Kenya

Franklin Simtowe
Alliance for Green Revolution in Africa (AGRA), Accra, Ghana

Elijah Muange
International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Nairobi, Kenya

Bernard Munyua
International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Nairobi, Kenya

Aliou Diagne
Africa Rice Centre, Cotonou, Benin

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Abstract

We apply a program evaluation technique to data obtained from rural Kenya to assess the patterns of adoption of improved pigeonpea varieties. The sample adoption rate of improved pigeonpea is found to be 36% while potential adoption rate is estimated at 48%. The adoption gap resulting from the incomplete exposure to the improved pigeonpea is 12%. Adoption is prominent among farmers that close to the agricultural offices, and among younger and wealthier farmers. The findings suggest that there is scope for increasing pigeonpea adoption once the farmers are exposed to the new technologies and once the associated constraints are addressed.

Key words: pigeonpea, adoption, Average Treatment Effect, Kenya

1 Introduction

Dryland legumes are believed to offer enormous opportunity for reducing food insecurity and poverty in the semi-Arid Tropics especially due to their adoptability to semi-arid conditions and their high likelihood to be adopted by the poor and vulnerable communities. Consequently the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), in collaboration with national partners, has developed and released a number of improved pigeonpea varieties as a way of improving pigeonpea productivity and competitiveness. In Kenya, varieties released and that are promoted for commercial production include; ICPL 87091 (a short-duration variety maturing in 3-4 months), KAT 60/8 (a medium-duration variety maturing in 5-6 months) and ICEAP 00040 (a long-duration variety maturing in 8-9 months). Prior to their full release, these improved varieties were introduced to farmers through participatory varietal selection (PVS), on-farm trials and demos and farmer field days. It was anticipated that farmers would continue disseminating them through their informal channels, such as the farmer-to-farmer exchange of seed and information.

In this study we attempt to understand the extent of diffusion of these improved varieties among the farming communities, the adoption and conditioning factors that lead to adoption or failure to adopt. Technology diffusion (awareness) is an important precondition for adoption to occur. However, in most cases exposure to a technology is not random. Individuals may be exposed to new technologies because they are targeted by researchers or extension workers based on the prejudice of their higher probability of adoption. Individuals may also through their private or self-interests and efforts get exposed to a new technology. These facts reinforce the fact that awareness of a technology by individuals is usually non-random and suffers from selection bias and hence the relationship between awareness and adoption cannot be linearly specified.

Previous studies (eg Shiferaw et al., 2008) have attempted to estimate adoption rates of improved varieties in Kenya. However, the adoption rates reported based on a sample of farmers in which some are unaware of the existence of improved varieties, are likely to under- estimate the true adoption rates. This is because, as expressed in Diagne and Demont (2007), such estimates suffer from non-exposure bias. One would think that the obvious fix to the non-exposure bias is to take the adoption rate within the subsample of farmers exposed to the technology, however, this too is not a consistent estimate of the true population adoption rate (even if the sample is random). This may underestimate or overestimate the true population adoption rate. In fact, the sample adoption rate among the exposed is likely to overestimate the true population adoption rate because of a positive population selection bias by which the subpopulation most likely to adopt gets exposed first. The reason for the positive population selection bias arises from two sources. The first is the farmer's self selection into exposure, reflecting the fact that exposure to a technology is partly the farmer's choice (Diagne and Demont 2007). The second source of selection bias results from the fact that some farmers (eg progressive farmers) and communities with a higher likelihood of adopting new technologies are targeted by extension workers and researchers for exposure (Diagne 2006).

Because of the non-exposure and selection biases, the causal effects of determinants of adoption can not be consistently estimated using classical adoption models such as probit, logit and tobit. Consistent with this notion, Besley and Case (1993) Saha et al (1994), and Dimara and Sakura (2003) show that the non-exposure bias also makes it difficult to interpret the coefficients of classical adoption models as the coefficients jointly measure the exposure and adoption. This fact makes the observed sample adoption rate to always underestimate the true population adoption rate when exposure of the population to the new technology is incomplete. We thus address the problem of estimation of the adoption rates and their determinants from a perspective of the treatment effects literature (Blundell and Costa Dias, 2000; Wooldridge, 2002; Moffit, 1991, Diagne and Demont, 2007).

The contribution of this paper to literature is largely empirical in that unlike the few previous studies that applied the framework on major staple crops such as rice largely in Western Africa; this study focuses on a relatively minor smallholder crop in the agricultural systems of the region: pigeonpea. While acknowledging the dynamic nature of technology adoption decisions, due to data limitations, the analysis presented in this paper is largely static, and thus does not look at the dynamics of adoption. The empirical question we would like to address is "what is the potential demand for improved pigeonpea cultivation in Kenya?

The Average Treatment Effect (ATE) framework is applied to data from 414 farmers in Kenya to provide a micro-perspective of the potential adoption rates and the determinants of adoption of improved pigeonpea varieties by the farmers. The paper is organized as follows: Section 2 presents a discussion on pigeonpea production and significance while the empirical framework for estimating adoption rates and their determinants is presented in section 3. Section 4, describes the sampling methodology and the data. The Results and discussions are presented in section 5, while section 6 concludes.

2 Pigeonpea Significance and production in Kenya

Kenya ranks fourth in global pigeonpea production after India, Myanmar and Malawi (FAOSTAT 2010). Available statistics (FAOSTAT 2010) show that between 1999 and 2008, area under pigeonpea in Kenya averaged at 175,191 hectares, while its average production was 89,351 metric tons per year. As shown in Table 1, pigeonpea accounts for about 14 percent of total area under pulses and 16 percent of total output of pulses in Kenya, making it the second important pulse after beans, in both area and production. The main products of pigeonpea are dry grain, green pods and fodder (Mergeai *et al.* 2001). Thus, the crop is primarily used as a cheap source of protein-rich food and fodder for poor smallholder farmers. Additionally, the stems of the crop are used as fuel wood, while its roots fix nitrogen into the soil and release soil-bound phosphorus, ameliorating the nitrogen and phosphorus deficiencies that typify most soils in the dry areas (Saxena 2008 and Shiferaw et al 2008).

Table 1: Mean area and production of key pulses in Kenya (1999-2008)

Crop	*Area (Ha)*	*% of total area under pulses*	*Production (tons)*	*% of total pulses production*
Beans	859,845	69	385,072	69
Pigeonpea	175,191	14	89,351	16
Cow peas	125,939	10	53,239	10
Other pulses	84,682	7	29,279	5

Source: Computed from ***FAOSTAT (2010).***

2.1 Pigeonpea Production in Kenya

Most of pigeonpea production in Kenya is concentrated in the semi-arid districts of Eastern Province (Olubayo *et al.* 2000), where it is important in local diets (Jones *et al.* 2002). To a lesser extent, it is also grown in Rift Valley, Central and Coast provinces of Kenya. The main producing Districts are Machakos, Makueni and Kitui, which account for more than two thirds of the total production (see for example, Shiferaw *et al.* 2008). Other important producing Districts are Mwingi, Mbeere, Tharaka and Meru.

Pigeonpea are categorised into three main types: the short duration type, which matures in 100-120 days; the medium duration type, which matures in 150-200 days; and the long duration type, which matures in more than 220 days (Jones et al 2002). Until the early 1980s there were no improved early-maturing varieties available to pigeonpea farmers in Kenya (Kimani 2001). However, collaborative research efforts between ICRISAT, the Kenya Agricultural Research Institute (KARI) and the University of Nairobi have in the recent past resulted in release of three such varieties, namely, ICPL 87091 (a short duration type released as *KARI Mbaazi 1*); KAT 60/8 (a medium duration type) and ICEAP 00040 – a long duration type released as *KARI Mbaazi II* (Shiferaw et al. 2008).

Notwithstanding these technological advances, many farmers still grow low-yielding, late-maturing landraces that take up to 11 months to mature in the field, while improved varieties are less common (Kimani 2001 and Mergeai et al, 2001). A recent study by ICRISAT (Shiferaw et al 2008) revealed that the proportion of households growing improved pigeonpea in two districts (Makueni and Mbeere) stood at 55 percent in 2005, while the percentage of pigeonpea area allocated to improved varieties by these households was 51 percent. This implies that there is still potential for promoting the adoption of improved varieties in the study areas, and indeed other important growing regions.

Production trends illustrated in Table 2 show that between 1999 and 2008, pigeonpea area increased from 145,000 to 196,000 hectares (35 percent increase), yet production increased more slowly, from about 71,000 to 84,000 tons (19 percent increase). This implies that the gains in production over the said period have been more attributable to area expansion than productivity increase.

Table 2: Pigeonpea Production Trends in Kenya (1999-2008)

Year	***Area (Ha)***	***Production (tons)***	***Yields (Tons/ha)***			
			Kenya	**Uganda**	**Malawi**	**Africa**
1999	145,311	70,651	0.49	1.00	0.73	0.69
2000	171,842	65,604	0.38	1.00	0.72	0.64
2001	164,001	73,463	0.45	1.00	0.78	0.69
2002	164,453	93,203	0.57	1.00	0.75	0.72
2003	183,612	98,280	0.54	1.00	0.79	0.72
2004	195,307	105,571	0.54	1.00	0.67	0.68
2005	180,240	96,092	0.53	1.00	0.41	0.60
2006	196,630	110,841	0.56	1.02	0.87	0.75
2007	154,554	95,637	0.62	1.02	0.99	0.83
2008	195,959	84,168	0.43	1.02	0.89	0.72
Average	**175,191**	**89,351**	**0.51**	**1.01**	**0.76**	**0.70**

Source: FAOSTAT (2010).

A further assessment reveals that over the same period, pigeonpea yields ranged between 0.4 and 0.6 tons/ha, averaging at 0.51 tons/ha. This compares poorly with other countries in the region such as Uganda and Malawi (1.01 and 0.76 tons/ha respectively), and Africa's average of 0.74 tons/ha. According to Kimani (2001) yields of up to 4.6 tons/ha have been achieved in on-farm varietal trials, implying that with decreasing land per capita, adoption of improved varieties by smallholder pigeonpea farmers is key to increasing their output and incomes. However, lack of seed and information on improved varieties, high cost of the seed when available, and pests and diseases constrain adoption of these varieties (Mergeai et al. 2001 and Shiferaw et al. 2008).

2.2 Pigeonpea utilization and marketing

Pigeonpea is harvested as green (vegetable) peas or dry grain and is produced for both home consumption and the market. According to Shiferaw et al (2008) vegetable peas account for approximately 40 percent of total pigeonpea production, of which 87 percent is consumed at the farm and 13 percent marketed. On the other hand, 60 percent of total pigeonpea production is harvested as dry grains, of which 67 percent is marketed and the rest consumed at farm level. There is significant demand for the crop both within and outside the country, as a result of which domestic and regional trade has developed (Jones et al. 2002). Market outlets for farmers are neighbours or rural consumers, rural and urban retail shops and open-air markets, urban supermarkets and exporters (Mergeai et al. 2001 and Shiferaw et. al 2008). The domestic market absorbs about 30 percent of marketed pigeonpea grain while the rest (about 70 percent) is exported, mainly to India (Shiferaw et. al 2008). However, according to Jones et al. (2002) marketing channels are characterised by high marketing and distribution costs and farmers receive the lowest share of final consumer prices, while urban processors receive the highest.

There exists an unexploited market for both dry and vegetable peas (Kimani 2001) but the greater proportion of pigeonpea produced in the country is still consumed locally. If the country is to benefit from these markets, it is imperative that farmers increase their marketable surplus by increasing their production. Although surplus pigeonpea production is highly dependent on availability of sufficient rainfall, annual grain exports to India in the last one decade recorded a high of just about 2,500 tons against an estimated demand of 15,000-20,000 tons from the Eastern Africa region (Shiferaw et al. 2008), implying that even under normal rainfall conditions, the country's marketable surplus falls short of the export demand. Therefore, if the factors constraining adoption of improved varieties available in the country are adequately identified and addressed, pigeonpea farmers would most likely increase their production, become more competitive in the global market and increase their earnings.

3 Empirical Framework

The analysis in this paper is guided by a theoretical framework of technology adoption under partial population exposure proposed by Diagne and Demont (2007). The framework is relevant in this analysis because although a number of pigeonpea varieties have been released and disseminated in Kenya, a very small fraction of the farming population has been exposed to the technologies. Furthermore, exposure to the improved pigeonpea by farmers was not random. Applying the treatment framework allows us to control for both non-exposure and selection biases and helps in estimating true population adoption rates and the determinants of adoption. The treatment variable in this paper is “exposure” or “awareness” of at least one variety of improved pigeonpea such that those exposed to improved pigeonpea are considered as “treated”, while those unaware are considered “untreated”.

First proposed by Rubin (1974) the average treatment effect (ATE) parameter measures the effect or impact of a “treatment” on a person randomly selected in the population (Wooldridge, 2002). In the context of this study “treatment” corresponds to exposure to a technology and the ATE on the adoption outcomes of population members is the population mean adoption outcome. This is the population mean adoption outcome when all members of the population have been exposed to a technology and it is, therefore, a measure of the intrinsic value of the technology as indicated by its potential demand by the population. In that sense, the population mean adoption outcome measured by the ATE parameter is the population mean *potential* adoption outcome.

The difference between the population mean potential adoption outcome and the mean actual (i.e. observed) adoption outcome, which is in fact the combined mean of population exposure to and adoption of the technology, is the population non-exposure bias. This is also known as the population *adoption gap*, because it measures in some sense the unmet population demand for the technology. It is assumed that the gap exists because of the incomplete diffusion of the technology in the population (Diagne and Demont 2007). Similarly, the mean adoption outcome in the exposed subpopulation corresponds to what is defined in the treatment effect literature as the *average treatment effect on the treated*, (i.e. the mean effect of a treatment in the treated subpopulation), commonly denoted as ATE1 or ATT (Wooldridge, 2002). The difference between the population mean adoption outcome (ATE) and the mean adoption outcome among the exposed (ATE1) is the population selection bias (PSB). The consistent estimation of ATE and ATE1, which are the main focus of the treatment effect methodology, requires controlling appropriately for the exposure status. The details of the estimation procedures of the ATE parameters in the adoption context are given in Diagne and Demont (2007).

Following Rosenbaum and Rubin (1983) and Wooldridge (2002), let y_1 be the potential adoption outcome of a farmer when exposed to improved pigeonpea varieties and y_0 be the potential adoption outcome[1] when not exposed to them. The "treatment effect" for the farmer i is the measure by the difference $y_{1i} - y_{0i}$. Hence the expected population adoption impact of exposure to the new varieties is given by the mean value $E(y_1 - y_0)$. However, as expressed by Diagne and Demont (2007) since exposure to a new variety is a necessary condition for its adoption, we have $y_0 = 0$ for all farmers not exposed. Hence the adoption impact of the farmer i is given by y_{1i} and the average adoption impact (of exposure) is given by $ATE = Ey_1$. The problem is that we observe y_1 only for the farmers exposed to the new varieties. In impact evaluation literature this is referred to as the problem of missing data. There is a problem of missing data because it is not possible to measure the impact on the same individuals, as at each moment in time, each individual is either under the intervention being evaluated or not and thus he or she can not be in both. This implies that we cannot observe the outcome variable of interest for the targeted individuals had they not been exposed to the new variety at the same time.

In this paper, let us assume the binary variable w to be an indicator for exposure to the improved varieties where $w = 1$ denotes exposure to at least one improved variety and $w = 0$, otherwise. The estimation of adoption rates and its determinants can be done based on the observed random vectors ((y_i, w_i, x_i, z_i) $i = 1, \ldots, n$) from a random sample of the population; where x_i is the vector of covariates that determines potential adoption outcome (the value of y_1) and z_i is the vector of covariates that determine exposure (the value of w_1) with the possibility of x_i and z_i having some common elements.

[1] In this study the adoption outcome is the adoption status (a dichotomous 0-1 variable).

The ATE methodology enables the identification and consistent estimation of the population mean adoption outcome $E(y_1)$ and the population mean adoption outcome conditional on a vector of covariates x $E(y_1 | x)$, which in this framework corresponds to the *conditional* population mean adoption outcome (ATE) denoted usually as ATE(*x*) (Wooldridge, 2002 chapter 18). One approach to the identification of ATE is based on the so-called conditional independence assumption (Wooldridge 2002, chapter 18) also referred to as the *ignorability* assumption, which states that the treatment status w is independent of the potential outcomes y_1 and y_0 *conditional* on the observed set of covariates z that determine exposure (w). This can be expressed as $P(y_i = 1 | w, z) = P(y_i = 1 | z); i = 0,1$.

The ATE parameters identified through the conditional independence assumption can be estimated from observed random vectors $(y_i, w_i, x_i, z_i)_{i=1,..,n}$ from a random sample of the population either using pure parametric regression based-methods where covariates are possibly interacted with treatment status variable (to account for heterogeneous impacts) or they are based on a two-stage estimation procedure where the conditional probability of treatment $P(w = 1 | z) \equiv P(z)$, called the propensity score, is estimated in the first stage and the ATE is estimated in the second stage by parameric or nonparametric methods (Diagne and Demont 2007).

In addition to the conditional independence assumption, it is assumed that potential adoption is independent from z, conditional on x: $P(y_1 = 1 | x, z) = P(y_1 = 1 | x)$. Thus we can be able to implement the estimation of adoption rate and its determinants from the exposed sub sample alone, if the conditional independence assumption holds and if potential adoption is independent of vectors of exposure determinants conditional on the vector of adoption determinants. Then the ATE (x) can be nonparametrically identified from the joint distribution of (y, z) condition on $w = 1$ by:

$$ATE\,(x) = \mathrm{E}\left(y \mid x, w = 1\right) \qquad \textbf{(1)}$$

This can be consistently estimated from a random sample of $y_i, x_i = 1,.....n$ drawn from the exposed subpopulation only.

The parametric estimation procedure of ATE is based on the following equation that identifies *ATE*(*x*) and which holds under the conditional independence (CI) assumption (see Diagne and Demont 2007):

$$ATE\,(x) = \mathrm{E}(y_1 \mid x) = \mathrm{E}(y \mid x, w = 1) \quad \textbf{(2)}$$

The parametric estimation proceeds by first specifying a parametric model for the conditional expectation in the right hand side of the second equality of equation (2) which involves the observed variables *y*, *x* and *w*:

$$E(y \mid x, w = 1) = g(x, \beta) \qquad \textbf{(3)}$$

where g is a known (possibly nonlinear) function of the vector of covariates *x* and the unknown parameter vector β which is to be estimated using standard Least Squares (LS) or Maximum Likelihood Estimation (MLE) procedures using the observations (y_i, x_i) from the subsample of exposed farmers only with *y* as the dependent variable and *x* the vector of explanatory variables. With an estimated parameter $\hat{\beta}$, the predicted values $g(x_i, \hat{\beta})$ are computed for all the observations *i* in the sample (including the observations in the non-exposed subsample) and ATE, ATE1 and ATE0 are estimated by taking the average of the predicted $g(x_i, \hat{\beta})$ $i=1,..,n$ across the full sample (for ATE) and respective subsamples (for ATE1 and ATE0):

$$A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n} g(x_i, \hat{\beta}) \qquad \textbf{(4)}$$

$$A\hat{T}E1 = \frac{1}{n_e}\sum_{i=1}^{n} w_i g(x_i, \hat{\beta}) \qquad \textbf{(5)}$$

$$A\hat{T}E0 = \frac{1}{n - n_e}\sum_{i=1}^{n} (1 - w_i) g(x_i, \hat{\beta}) \qquad \textbf{(6)}$$

The effects of the determinants of adoption as measured by the *K* marginal effects of the *K*-dimensional vector of covariates *x* at a given point $\bar{x}$ are estimated as:

$$\frac{\partial E(y_1 \mid \bar{x})}{\partial x_k} = \frac{\partial g(\bar{x}, \hat{\beta})}{\partial x_k} \qquad k = 1,..,K \qquad \textbf{(7)}$$

where x_k is the k^{th} component of *x*.

In our empirical analysis below, we have estimated the ATE, ATE1, ATE0, the population adoption gap ($G\hat{A}P = J\hat{E}A - A\hat{T}E$)[2], and the population selection bias ($P\hat{S}B = AT\hat{E}1 - A\hat{T}E$) parameters using the parametric regression based estimators (equations 4, 5, and 6).

The estimation of the determinants of exposure is important for its own sake as it can provide valuable information regarding the factors influencing farmers' exposure to a new technology. These factors, which are mostly related to the diffusion of information, can very well be different from those influencing the adoption of the technology once exposed to it. In our estimation of the parametric regression based estimators, since y is a binary variable, equation 3 above is effectively a parametric probabilistic model. We, therefore, have $E(y \mid x, w=1) = P(y=1 \mid x, w=1)$ with an assumption of a probit model, $g(x, \beta) = \Phi(x\beta)$. In this case the parametric estimation of ATE reduces to a standard probit estimation restricted to the exposed sub-sample. The marginal effects in equation (7) are also estimated using this ATE parametric model. The estimation was done in STATA (for details see Diagne and Demont 2007).

4. Data

The data used in this analysis were collected by the International Crops Research Institute for the semi-Arid Tropics (ICRISAT), in collaboration with the Kenya Agricultural Research Institute (KARI) between August and September 2008, in Kenya. The data were collected through a household survey conducted in Makueni and Mbeere districts in Eastern Province of Kenya. The total population was estimated at 839,155 and 110, 503 persons for Makueni and Mbeere respectively, in 2002. Poverty in both districts remains a key development challenge, with about 73 and 65 percent of the total population in Makueni and Mbeere respectively, being classified as poor (Republic of Kenya (2002a, 2002b, 2005a and 2005b).

A multi stage sampling procedure was employed in selecting households for the survey. The first stage involved a purposeful sampling of two districts where pigeonpea are grown. The

[2] Note that as discussed earlier, the joint exposure and adoption parameter (JEA) is consistently estimated by the sample average of the *observed* adoption outcome values: $J\hat{E}A = \frac{1}{n}\sum_{i=1}^{n} y_i$.

second stage involved a random selection five main pigeonpea producing Divisions[3]: three in Makueni and two in Mbeere. Similarly, two Locations were randomly selected from the key pigeonpea producing Locations within the sampled Divisions, making a total of ten (10) Locations. Further, in each selected Location, three villages were randomly selected, making a total of thirty (30) villages (18 from Makueni and 12 from Mbeere). Finally, in each of the sampled villages, a random sample of the respondent households was drawn from a list of farming households obtained from the village headman. The total number of respondent households sampled in each division, location and village was weighted by the total number of households in the corresponding administrative unit. A total of 414 households were successfully sampled and surveyed (257 from Makueni district and 157 from Mbeere district).

Data collected included household composition and characteristics, land and non-land farm assets, livestock ownership, household membership in different rural institutions, farmer knowledge and cultivation of improved varieties, inputs used, costs of production, yield data for different crop types, indicators of access to infrastructure, household market participation, household income sources and major consumption expenses, for the 2006/07 cropping season. Prior to the survey a list of known modern and traditional varieties in the village was constructed and each farmer selected for the survey was asked whether he or she knew each of the varieties and crops. If the answer to the question was a 'yes' then the farmer was asked whether they had ever cultivated the variety and if they cultivated it in 2006/07 season. In this study we define knowledge or exposure to a variety as a 'yes' answer to the first question and adoption as the cultivation of the variety.

Farm household characteristics

Table 3 reports descriptive statistics disaggregated by their adoption status for 414 surveyed farmers. Adopters are defined as households that planted at least one improved variety of pigeonpea during the 2007/08 cropping season. Results show that improved pigeonpea varieties were grown by 148 households, representing 36 percent of the total sample. About one quarter-of surveyed households were female-headed and there were no significant differences in the distribution of the gender of household head between adopters and non-adopters. The average age of the household head was about 46.7 years, but the heads of adopting households were significantly younger (44 years) than those of the non-adopting households (48 years). On

[3] Administratively, Kenya is divided into 8 Provinces. Under each Province, we have several Districts, each of which is divided into Divisions. Divisions are divided into Locations, each comprising of several Sub-locations. Sub-locations are then divided into the lowest administrative units called Villages.

average, the household size for the sample was 6 persons but adopting households were generally larger (6.5 members) than non-adopting households (5.96 members). The size of land owned by each surveyed household was about 2.0 ha, with adopting households cultivating significantly larger parcels of land (2.4 ha) than the non-adopting households (1.8 ha). Household wealth status was fairly comparable between adopters and non-adopters. For instance, the mean value of non-livestock assets (KSh 13,566) did not show any significant differences between the adopting and non-adopting households.

Table 3: Household characteristics by adoption status of improved pigeonpea in 2007/08

Characteristic	*Non-adopters (N=296)*	*Adopters (N=148)*	*Total (N=414)*	*Difference*
Socio-demographic factors				
Proportion of female headed households (%)	25.8	25.2	25.5	0.6
Age of the household head (years)	48.1	44.3	46.7	3.8***
Household size (total number of persons)	5.9	6.5	6.1	-0.6**
Total own land (ha)	1.8	2.4	2.0	-0.6**
Value of non-livestock assets excluding land (Ksh)	14,392	13,036	13,566	1,356
Annual peracpita expenditure(Ksh)	21,448	23,216	22,081	-1,768
Education and experience in farming				
Education level of the household head (years)	6.6	6.9	6.7	-0.3
Cumulative household education (years)	31.3	35.1	32.7	-3.8*
Experience of growing pigeonpea (years)	16.8	13.9	15.7	2.9**
Institutional factors				
Distance to the nearest agricultural office (km)	18.8	12.9	16.7	5.7***
Distance to the nearest main market (km)	6.7	6.7	6.7	0.0
Contact with government extension agent (% households)	38.2	55.8	44.5	-17.5***
Contact with NGO extension agent (% households)	15.5	26.5	15.5	-11.0***
Got some credit (% households)	17.1	24.5	19.7	-7.4*
Membership to farmer/community group (% households)	87.9	0.93.2	89.8	-5.3
Number of groups the household belongs to	1.8	2.0	1.9	-0.2**
Knowledge and adoption of improved varieties				
Knowledge of improved pigeonpea varieties (% households)	60.2	100	74.5	-39.8***
Area under pigeonpea (ha)	0.74	0.98	0.83	-0.24**
Cultivation of local pigeonpea varieties (% households)	88.3	62.1	78.9	26.3***
Area under local pigeonpea varieties (ha)	0.70	0.54	0.65	0.16**

*, ** and *** Indicate that difference between adopters and non-adopters is statistically significant at 10, 5 and 1 percent level respectively (t-tests are used for differences in means).
Source: Survey Data 2008.

Household heads in the sample were generally fairly literate: the average number of years of formal education for each interviewed household head was 6.7 years, and there was no significant difference between adopters and non-adopters. Conversely, the total stock of years of formal education and experience in pigeonpea farming, which averaged at 32.7 and 15.7 years respectively, varied significantly between adopters and non-adopters. There were remarkable differences in access to agricultural information sources between adopting and non-adopting households. For example, a larger proportion of adopters (55.8 percent) had accessed government extension services in the study season compared to non-adopters (44.5 percent). This could be partially explained by the fact that adopters generally reside closer to government agricultural extension office (12.9 km) compared to non-adopters (18.8 km), a finding also reported by Kibaara et al (2009). Similarly, a significantly larger proportion of adopters accessed agricultural information through NGO extension agents compared to non-adopters. An overwhelming majority (89.8 percent) of surveyed households belonged to at least one social group, with most households belonging to about 2 such groups. However, adopting households belonged to significantly more groups (2.0) than non-adopters (1.8).

Exposure to improved pigeonpea varieties among the interviewed households was generally high. About 75 percent of the households had some knowledge about the improved varieties. While all adopters were exposed to improved varieties, only 60 percent of non-adopters had been exposed. Despite the high level of exposure, close to 80 percent of the households continue to grow local varieties, although cultivation of these varieties is significantly lower among adopters (62 percent) compared to non-adopters (88 percent).

5.0 Results and Discussions

5.1 Knowledge, and Adoption of Improved Pigeonpea Varieties in the Study Area

Over the last two decades, several improved varieties have been promoted in the study area. These include ICPL 87091, ICEAP 00040, ICEAP 00068, ICEAP 00557, ICEAP 00554, KAT 60/8 and ICEAP 00777. In this study, respondents were asked to provide information about the crop varieties that they knew, and as already reported in Table 3, about 75 percent of the respondents are aware of at least one improved variety of pigeonpea. Knowledge of improved pigeonpea varieties is more prevalent in Mbeere (77 percent) than in Makueni (73 percent), but this difference was not statistically significant.

Table 4 shows the proportion farmers that reported having some knowledge of each of the improved varieties. The results reveal that ICPL 87091 is the most widely known (53 percent) followed by ICEAP 00040, known only by 16 percent of the farmers. The rest of the varieties are each known by less than 10 percent of the farmers. Another finding was that a significant proportion of farmers who knew the improved varieties did not adopt them in the season under study. This implies that knowledge of improved varieties is a necessary but not sufficient condition for adoption of the varieties. Generally, these results show there is a gap in knowledge of improved pigeonpea varieties, which presents an opportunity for ICRISAT to use existing structures for government extension services to disseminate the information to farmers in potential pigeonpea growing areas.

Many respondents expressed awareness of the improved varieties, but not all have ever grown or continue to grow them. For instance, although 53 percent of the farmers expressed some knowledge of the short duration variety ICPL 87091, only 44 percent of them had ever grown it, and 27 percent actually grew it in the reference season. Similarly, the long duration variety ICEAP 00040 was known by 16.3 percent of farmers, but only 69 percent of them had ever grown it and a much smaller proportion (61 percent) grew it in the study season. These results indicate that depending on prevailing circumstances, some of the farmers who adopt improved pigeonpea varieties in one season dis-adopt them in other seasons. This further points to the need for the identification and easing of factors that constrain consistent adoption of improved varieties, if the benefits of adoption are to be sustained.

Table 4: Knowledge, Diffusion and Adoption of Improved Pigeonpea Varieties

Variety	***Know the variety***	***Ever adopted variety***		***Adopted variety in 2007/08 season***	
		% total sample	% of exposed	% total sample	% of exposed
ICPL 87091	52.8	23.1	43.8	14.4	27.2
ICEAP 00040	16.3	11.2	68.7	10.0	61.2
ICEAP 00068	8.8	5.4	61.1	4.6	52.8
ICEAP 00557	8.5	6.6	77.1	5.4	62.9
ICEAP 00554	5.8	4.4	75.0	3.6	62.5
KAT 60/8	3.6	2.7	73.3	2.4	66.7
ICEAP 00777	0.7	0.2	33.3	0.2	33.3
At least one improved variety	*74.5*	*45.0*	*60.5*	*35.8*	*48.0*

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)

Although overall adoption rates may be calculated for the entire sample, these may not provide a reliable estimate of the population adoption rates due to the non-random nature in which farmers get exposed to the varieties. Therefore, these sample adoption rates are likely to be biased downwards because they include farmers who were not yet exposed to the varieties and therefore they cannot adopt unless exposed. In fact some farmers would have adopted the improved pigeonpea varieties if they had been exposed to them, but in this sample adoption rates, they are considered as non adopters. Therefore, an assessment of adoption rates among the exposed sub-population appears more appealing in terms explaining the potential adoption rates because it somehow addresses the problem of non-exposure bias. As shown in Table 5, the adoption rate among the sub-sample of farmers that were aware of improved pigeonpea is higher than the adoption rates for the whole sample. The overall adoption rate for at least one improved pigeonpea variety among the sub-sample of exposed farmers in Oct/Nov 2007/08 season was 31.4 percent compared to a lower adoption rate of 23.8 percent for the whole sample.

5.2 Determinants of exposure to improved pigeonpea varieties

In this study, about 75% of the sample households were exposed to at least one of the improved pigeonpea varieties. Based on this information, we estimate a probit regression of factors that affect the propensity of exposure to improved varieties of pigeonpea. Table 5 depicts results from a probit estimation of the determinants of the probability of getting exposed to at least one improved pigeonpea varieties. Several variables show statistically significant coefficients at 5% level.

The variable capturing access to markets (the distance to the nearest village market) returned a negative and expected sign and it was significant at 1% level. The coefficient for the number of years of residence in a village is positive and significant suggesting that the propensity of exposure to improved varieties increases with the number of years of residence in the village. This also provides evidence of the significance of social capital in information sharing. The coefficient for gender of the household head is negative and significant at 10% level indicating that women have a higher propensity to be exposed to improved varieties of pigeonpea. A negative and significant coefficient for the age of the household-head indicates that younger farmers have a higher propensity to get exposed to improved varieties of pigeonpea. Furthermore, results indicate that farmers with larger land holdings easily get exposed to improved varieties than those with smaller land holdings.

Table 5: Determinants of the of probability of exposure to improved pigeonpea in Kenya

Variables	Coefficient		Marginal effects	
	Coeff	Std. Err	dy/dx	Std. Err
District dummy (1=Mbeere, 0= Makueni)	0.1683	0.1876	0.0526	0.0586
Distance to the main market (km)	-0.005	0.0148	-0.0017	0.0046
Number of years of residence in the village	0.0159***	0.0050	0.0050***	0.0016
Distance of the agricultural office (km	0.0015	0.0042	0.0005	0.0013
Gender of household head(1=male, 0= female)	-0.3567**	0.1775	-0.1043**	0.0480
Age of the head of household (yrs)	-0.0147**	0.0062	-0.0046**	0.0020
Education level of head of household (yrs)	0.0247	0.0218	0.0077	0.0068
Household size (total number of persons)	0.0148	0.0298	0.0047	0.0093
Land holding size (acres)	0.0746**	0.0348	0.0233**	0.0108
Membership in a farmer group (1=yes, 0= otherwise)	-0.1365	0.2605	-0.0410	0.0750
Constant	0.7715	0.5485		
Number of interviews	414			
Pseudo R2	0.15			
LR Chi ^{2}	70.95			

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)
Key : * p<0.10; ** p<0.05; *** p<0.01

The proxy variable for access to agricultural extension i.e contact with government extension workers where information on improved varieties is access returned a significant and positive coefficient. The findings highlight the significant role of government as source of variety information or as a provider of extension services, particularly for pigeonpea. Most pigeonpea varieties are disseminated through field days and participatory variety selection, and government extension workers play an important role in such activities. The coefficients for education, household size and ownership of communication device such as radio, phone, and television were not significant.

5.3 Adoption rates for improved Pigeonpea and their Determinants

5.3.1 Adoption rates for improved pigeonpea

Table 6 presents the results of the actual (JEA) and potential (ATE) adoption rates of the improved pigeonpea varieties, and also the adoption gap generated by the incomplete diffusion of the new technologies in 2007/08. The ATE means the effect or the impact of a “treatment” on a person randomly selected in the population. In the context of this study, a “treatment” corresponds to exposure to the improved pigeonpea varieties, and the ATE on the adoption outcomes of the population members is the (potential) population adoption rate. That is, the adoption rate when all farmers have been exposed to the improved pigeonpea varieties.

The diffusion results show that about 75% of farm households were aware of at least one improved pigeonpea variety in 2007. This incomplete diffusion of the improved pigeonpea varieties restricted the actual adoption (JEA) rate of at least one improved variety to about 36%, whereas the potential adoption rate (ATE) was 48% in the same year. Thus when compared to the sample adoption rate of 36%, there is a substantial population adoption gap of 12% due to the population’s incomplete exposure to the improved pigeonpea varieties. The estimated adoption gap is statistically significantly different from zero at 1% level. This finding implies that there is potential for increasing the adoption rate by 12% once all farmers become aware of at least one improved pigeonpea variety and once other constraints such seed and cash are addressed.

The results of ATE1, which is by definition, the average treatment effect on the treated, show that among the sample population, 49% of farm households exposed to the improved pigeonpea varieties adopted at least one of them. The non-exposed (untreated) subpopulation mean potential adoption rate, given by ATE0 is estimated at 48%. The estimated population selection bias which is measured by the difference in the potential adoption rate in the exposed sub-population and the consistently estimated population adoption rate is estimated at 0.2% and it is statistically insignificant from zero. This insignificant selection bias suggests that the adoption probability for a farmer belonging to the sub-population of informed farmers is the same as the adoption probability for any farmer randomly selected from the whole population.

Table 6: Adoption rates and adoption gap of the improved pigeonpea technology in 2008 for the whole sample (n=414)

Estimator	Parameter	Std. Err.	Z	P>|z|
Proportion of exposed households	0.7441	0.0215	34.64	0
ATE(potential adoption rate)	0.4861	0.0262	18.57	0
ATE1(adoption rate among exposed sample)	0.4883	0.0258	18.95	0
ATE0 (adoption rate among non-exposed)	0.4796	0.0304	15.77	0
Joint exposure and adoption rate (JEA)	0.3633	0.0192	18.95	0
Adoption gap (GAP=ATE-JEA)	-0.1228	0.0078	-15.77	0
Population Selection Bias(PSB)	0.0022	0.0039	0.56	0.5

5.4 Determinants of adoption of improved pigeonpea varieties

Results on the determinants of improved pigeonpea adoption for the classic “adoption” model, and ATE probit model are presented in Table 7. There are striking differences in the magnitude of the coefficients between the two models. The observed findings are consistent with the theoretical expectation in that as reported by Diagne and Demont (2007), the conditional mean “adoption” function estimated in the classical adoption model is equal to the true population average conditional adoption function (the “true” population adoption function) multiplied by the probability of being aware of the technology. Hence, for a factor determining adoption alone and not awareness, its marginal effect calculated from the classical “adoption” model is equal to its marginal effect from the true adoption model multiplied by the conditional probability of awareness, a quantity always between 0 and 1 and usually very small when not many farmers are aware of the technology. It is also important to note that some coefficients are significant in both models while some are significant only in the ATE probit model.

Results show that factors such as the age of the of the head of household, distance to agricultural office, the land holding size, education, household size, and value of asset, among others, have a significant effect on the adoption of improved pigeonpea varieties.

Table 7: Determinants of adoption of improved pigeonpea- Estimated coefficients

Variables	Coef.	Std. Err.	z	P>z
District dummy (1=Mbeere, 0= Makuwen1)	0.9633**	0.3844	2.51	0.012
Distance to the main market (km)	-0.0112	0.0378	-0.3	0.766
Number of years of residence in the village	-0.0042	0.0091	-0.46	0.643
Distance of the agricultural office (km	-0.0369***	0.0095	-3.86	0.000
Gender of household head(1=male, 0= female)	0.3573	0.3064	1.17	0.244
Age of the head of household (yrs)	-0.0253**	0.0124	-2.04	0.042
Education level of head of household (yrs)	-0.0779*	0.0418	-1.86	0.062
Household size (total number of persons)	0.1240**	0.0548	2.26	0.024
Land holding size (acres)	0.8369***	0.2806	2.98	0.003
Membership in farmer group (1=yes, 0= otherwise)	0.6803	0.4710	1.44	0.149
Total livestock units	-0.0322	0.0397	-0.81	0.418
Access to formal credit (1=yes, 0=no)	0.0845	0.4315	0.2	0.845
Constant	-0.8841	1.0637	-0.83	0.406
Number of interviews	299			
Pseudo R2	0.13			
Wald Chi ^{2}	47.7			

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)
Key : * $p<0.10$; ** $p<0.05$; *** $p<0.01$

The coefficient for distance to an agricultural office is negative and significant at 1% level suggesting that farmer-proximity to an agricultural office increases the propensity to adopt improved pigeonpea. The intuition drawn from such a finding is that formal ways of promoting the adoption of technology such as through a government extension system (eg Participatory Variety Selection) are quite relevant in Kenya in as far as the promotion of pigeonpea production.

The coefficient for the age of the head of household is negative and significant at 5% suggesting that the probability of adopting at least one improved pigeonpea variety diminishes with old age. Adoption literature largely shows that the impact of the age of a farmer on adoption can not be pre-determined because older farmers are sometimes considered to be risk-averse and thus less willing to try new innovations than younger farmers. The other strand of literature considers older farmers as experienced and, therefore, in a better position to make sound judgment regarding the adoption of new technologies, suggesting that older farmers will be quick to adopt improved technologies that offer better returns than younger and inexperience farmers. Therefore, the negative effect of age on adoption can also be interpreted in terms of the risk-aversion paradigm assuming that farmers consider the new technologies to be riskier than older technologies that they have been growing for a long period of time. However, one other possible explanation for the negative coefficient can be drawn from the innovation diffusion paradigm which largely assumes that technology is technically and culturally appropriate but the problem of adoption is one of asymmetric information and very high search costs (Feder and Slade, 1984). Therefore, older farmers may incur higher search costs for the new technologies, hence lack information on their existence and hence fail to adopt them.

In contrast to prior expectation, the coefficient for education of the head of households returned a negative sign suggesting that improved pigeonpea is mainly adopted by the less educated. There are a number of reasons why the less educated may prefer growing certain crops. In the case of pigeonpea, this may be attributed to the fact that the crop is pro-poor and that well educated people may prefer to invest in more profitable crops than pigeonpea.

A number of wealth related variables returned significant and expected coefficients. The size of the land owned by the household returned a positive and significant coefficient suggesting that farmers with larger holdings are more likely to adopt improved varieties than those with smaller holdings. Also consistent with the economic constraint paradigm of adoption models, we find that access to credit returned an expected positive and significant coefficient, suggesting that agricultural credit in Kenya can have a significant impact in facilitating the adoption of improved pigeonpea varieties. This implies that there exists a great scope for increasing the cultivation of improved pigeonpea through an improved access of farmers to equity.

The ownership of a bicycle returned a positive and significant coefficient suggesting that households that own bicycles have a higher propensity to adopt improved varieties of pigeonpea than those that do not own a bicycle. The ownership of a bicycle may enhance technology adoption as it facilitates an individual's movement and consequently access to technologies such as seed, however it may also be an indicator of a wealthier household that has the equity required to purchase related inputs such as seed. In this study, since the ownership of the bicycle had no effect on the status of farmer's awareness of the improved varieties, this may suggest that the ownership of a bicycle is merely a wealth indicator variable which proxies the household's ability to acquire inputs required for the adoption of improved pigeonpea varieties.

In general the significance of wealth related variables may also explained by the economic constrain paradigm of adoption models which states that input fixity in the short run, such as access to credit, land, labor or other critical inputs limits production flexibility and conditions technology adoption decisions (Uaiene et al. 2009). One constraint to pigeonpea cultivation is the lack of seed. The positive coefficient for most of the wealth related variable may therefore be explained by the fact that economically well-off farmers have the necessary equity to acquire seed and other complementary inputs than poorer farmers.

The proxy variable for access to markets (distance to the village market and distance to the main market) were insignificant, while the distance to the agricultural extension office retuned significant and expected sign of the coefficient. The results indicate that adoption is more likely to occur among households that are further close to the agricultural extension office.

The coefficient for the size of the household is positive and significant implying that labour abundant household have a higher propensity to adopt improved varieties than smaller households. Larger households also have an added advantage in that the larger the number of individuals in the household, the higher the probability of at least one member of the household to get exposed to improved seed varieties of pigeonpea.

6. Conclusions

This paper has provided estimates of actual and potential adoption rates and the determinants of adoption for the improved pigeonpea varieties in Kenya and has shown the importance of appropriately controlling for exposure and selection bias when assessing the adoption rates of a technology and its determinants. We find that improved pigeonpea adoption rates in Kenya could have been up to 48% in 2007 instead of the observed sample adoption rate of 36% if the whole population was exposed to the improved pigeonpea varieties by the year 2007. The non-exposure bias of 12% suggests that there is potential for increasing the adoption rate of improved pigeonpea by 12% if its diffusion to the population can be completed.

About 75% of the sampled households expressed awareness of the improved varieties of pigeonpea. While most of the information on improved pigeonpea appears to be disseminated through informal means such as farmer- to- farmer exchange of information, there is a huge potential of using existing formal institutions and methods in the dissemination of information on improved pigeonpea. The formal methods that have proven to be effective are already in place and they include on-farm trials, demonstration plots controlled by agricultural extension agents, field days for farmers, and agricultural shows to which farmers are invited.

Furthermore, the study has shown that the exposure to improved pigeonpea varieties and their adoption by farmers is influenced by a number of other factors and that in some cases; factors affecting the two outcomes (exposure and adoption) are different. Signifying the presence of economic constraints, the study has shown that the propensity of cultivating (adopting) at least one improved pigeonpea variety is high among farmers that have access to equity and that are wealthier. These findings point to the importance of improving farmer's access to financial markets that enable them to acquire credit to purchase seed and complementary inputs for improved pigeonpea. The policy implication is that supporting farmers with credit and extension services would significantly increase their participation in the cultivation of improved pigeonpea varieties.

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