



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Determinants of Agricultural Technology Adoption: The Case of Improved Pigeonpea Varieties in Tanzania

Franklin Simtowe

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

Menale Kassie

International Maize and Wheat Improvement Center, Nairobi, Kenya

Aliou Diagne

The Africa Rice Centre, Cotonou, Benin

Solomon Asfaw

Food and Agricultural Organization of the United Nations (FAO), Rome, Italy

Bekele Shiferaw

International Maize and Wheat Improvement Center, Nairobi, Kenya

Said Silim and Elijah Muange

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

Abstract

If dryland legumes are to meet the expectations of reducing poverty and hunger in the semi-arid tropics, there will be need for a full understanding of their potential for diffusion and the barriers to adoption. We apply a program evaluation technique to data obtained from Tanzania to derive estimates of the *actual* and *potential* adoption rates of improved pigeonpea varieties and their determinants. The study reveals that only 33% of the sampled farmers were aware of the improved pigeonpea varieties which consequently restricted the sample adoption rate of improved varieties to only 19%. The potential adoption rate of improved pigeonpea if all farmers had been exposed to improved varieties is estimated at 62% and the adoption gap resulting from the incomplete exposure of the population to the improved pigeonpea is 43%. We further find that the awareness of improved varieties is mainly influenced by attendance of Participatory Variety Selection activities. The adoption of improved varieties is more pronounced among farmers with smaller landholdings suggesting that farmers facing land pressure intensify pigeonpea production through the adoption of improved high yielding varieties. The findings are indicative of the relatively large demand for improved pigeonpea varieties suggesting that there is scope for increasing their adoption rate in Tanzania once the farmers are made aware of the existence of the technologies.

Keywords: pigeonpea, adoption, average treatment effect, Tanzania

JEL: C8, O3, Q12, Q16

1 Introduction

The adoption of improved agricultural technologies continues to be seen as an important route out of poverty in most of the developing world. Yet, as expressed by BANDIERA and RASUL (2006) agricultural innovations are often adopted slowly and several aspects of adoption remain poorly understood. A plethora of scholarly literature reports on a number of constraints to adoption, such as extreme weather, liquidity constraints, awareness of technologies (DIAGNE and DEMONT, 2007), risk aversion (KOUNDOURI et al., 2006), institutional constraints, lack of human and financial capital, and lack of infrastructure (FEDER et al., 1985, and FOSTER and ROSENZWEIG, 1995). These are considered as potential explanations for low adoption of improved agricultural technologies.

Our motivation derives from the empirical evidence of the importance of creating awareness of a new technology in generating its demand and consequently adoption (ROGERS, 1995). Classical adoption literature states that the perceived attributes of the technology condition adoption behaviour of farmers. Once exposed to (made aware of) the technology, farmers gather information about technology attributes which will guide them in deciding whether or not to adopt it. As reported by ASHBY and SPERLING (1995) with full information about a technology, farmers may subjectively evaluate the technology differently than scientists. Thus, awareness is an important precondition for adoption to occur. 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/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. This suggests that the relationship between awareness and adoption cannot be linearly specified.

A related problem is that when a technology is new and the target population is not universally exposed to it, the observed sample adoption rate is not a consistent estimator of the true population adoption rate. It suffers from what is known as “non-exposure”¹ bias and it yields inconsistent and biased estimates of population adoption rates even when based on a randomly selected sample (DIAGNE and DEMONT, 2007).

¹ The non-exposure bias results from the fact that farmers who have not been exposed to a new technology cannot adopt it even if they might have done so if they had known about it (DIAGNE, 2006).

In this article we analyze the decision to adopt improved pigeonpea varieties by farmers in Northern Tanzania. In the study area, although a number of pigeonpea varieties have been released, they have not been widely disseminated and thus a very small fraction of the farming population has been exposed to them. As a consequence, we do not expect high adoption rates of these varieties by farmers randomly sampled from the study area. However, the interest in this paper is to assess the potential for adoption of these technologies by the farming population once fully disseminated. As expressed in DIAGNE and DEMONT (2007) 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 (e.g. 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 SKURAS (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. The empirical question we would like to address is what is the potential demand for improved pigeonpea cultivation in Tanzania? The Average Treatment Effect (ATE) framework is applied to data from 613 farmers in Tanzania to provide a micro-perspective of the potential adoption rates and their determinants of adoption of improved pigeonpea varieties. 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 The Significance of Pigeonpea and its Production in Tanzania

Pigeonpea (*Cajanus cajan*) is an important multi-use shrub legume of the tropics and subtropics. The crop originated from India and moved to Africa about 4,000 years ago. Unlike other grain legumes, pigeonpea production is concentrated in developing countries, particularly in a few South and Southeast Asia and Eastern and Southern African countries. It is the preferred pulse crop in dryland areas where it is intercropped or grown in mixed cropping systems with cereals or other short duration annuals (JOSHI et al., 2001). 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).

Tanzania is one of the major growers and exporters of pigeonpea. The crop accounts for about 5% of total output of pulses and 4% of total area under pulses, making it the third most produced pulse after beans and cow peas in the country. Production trends (FAOSTAT, 2010) show that between 1999 and 2008, pigeonpea area increased from 65,000 to 67,500 hectares (3.8%) and output from about 47,000 to 48,500 tons (3.2%). On the other hand, the crop's yields remained relatively constant at about 0.72 tons/ha, implying that the gains in production over the said period have been attributable to area expansion and not productivity increase. While these yields compare favourably with those of Malawi, a neighbouring country (0.76 tons/ha), and Africa's average of 0.74 tons/ha, this is still below the crop's potential of up to 4.6 tons/ha for improved varieties obtained in on-farm trials (KIMANI, 2001), implying that by increasing adoption of improved varieties, smallholder pigeonpea farmers in Tanzania can increase their output without necessarily cultivating additional land.

Since 1986, collaborative efforts between ICRISAT and the National Agricultural Research systems in Tanzania have seen development and release of short duration variety ICPL 87091 (released as *Kombo* in 1999); long duration variety ICEAP 00040 (released as *Mali* in 2002) and medium duration variety ICEAP 00068 (released as *Tumia* in 2003) (KIMANI, 2001, and SHIFERAW et al., 2005). Through the screening

program for *fusarium* resistance initiated by ICRISAT in collaboration with partners Tanzanian, fusarium-resistant improved pigeonpea (FRIP) variety (ICEAP 00053), which embodies farmer and market-preferred traits was released for dissemination to farmers. Nonetheless, these research efforts do not seem to have produced desired adoption outcomes among the farming communities. 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, 2001). For instance, the study by SHIFERAW et al. (2005) in Babati, the main producing district, reported that while over 80% of pigeonpea farmers grew local varieties, only 32% of the farmers grew improved varieties. This paper explores some key impediments to the adoption of improved varieties and potential for scaling up the adoption of such varieties.

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 they have not been widely disseminated and thus a very small fraction of the farming population is aware of their existence. 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 popu-

lation 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 (2001), let y_1 be the potential adoption outcome of a farmer when exposed to improved pigeonpea varieties and y_0 be the potential adoption outcome² when not exposed to them. The “treatment effect” for the farmer i is the measure by the difference $y_{i1} - y_{i0}$. 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_{i1} and the average adoption impact (of exposure) is given by $ATE = Ey_1$. The problem is that we only 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 $((y_i, w_i, x_i, z_i))_{i=1, \dots, n}$ from a random sample of the population; where x_i is the vector of covariates that determines potential

² In this study the adoption outcome is the adoption status (a dichotomous 0-1 variable).

adoption outcome (the value of y_1) and z_i is the vector of covariates that determine exposure (the value of w_i) with the possibility of x_i and z_i having some common elements.

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 $P(y_j = 1 | w, z) = P(y_j = 1 | z); j = 0, 1$.

The ATE parameters identified through the conditional independence assumption can be estimated from observed random vectors $(y_i, w_i, x_i, z_i)_{i=1, \dots, n}$ 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 parametric 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:

$$(1) \quad ATE(x) = E(y | x, w = 1)$$

This can be consistently estimated from a random sample of $y_i, x_i, i = 1, \dots, n$ 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):

$$(2) \quad ATE(x) = E(y_1 | x) = E(y | x, w = 1)$$

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 :

$$(3) \quad E(y | x, w = 1) = g(x, \beta)$$

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 $g(x_i, \hat{\beta})$ $i=1, \dots, n$ across the full sample (for ATE) and respective subsamples (for ATE1 and ATE0):

$$(4) \quad \hat{ATE} = \frac{1}{n} \sum_{i=1}^n g(x_i, \hat{\beta})$$

$$(5) \quad \hat{ATE1} = \frac{1}{n_e} \sum_{i=1}^n w_i g(x_i, \hat{\beta})$$

$$(6) \quad \hat{ATE0} = \frac{1}{n - n_e} \sum_{i=1}^n (1 - w_i) g(x_i, \hat{\beta})$$

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:

$$(7) \quad \frac{\partial E(y_1 | \bar{x})}{\partial x_k} = \frac{\partial g(\bar{x}, \hat{\beta})}{\partial x_k} \quad k = 1, \dots, K$$

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 $(\hat{GAP} = \hat{JEA} - \hat{ATE})^3$, and the population selection bias

³ 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: $\hat{JEA} = \frac{1}{n} \sum_{i=1}^n y_i$.

($P\hat{S}B = ATE1 - ATE$) 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 $E(y|x, w=1) = P(y=1|x, w=1)$ 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 DAIGNE 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 Selian Agricultural Research Institute (SARI) between November and December 2008, in Tanzania. The data were collected through a household survey conducted in four key pigeonpea growing districts of the Northern Zone: Kondoa, Karatu, Babati and Arumeru. In each district, three major pigeonpea growing divisions were selected and two wards sampled in each of the divisions. Twenty five farmers were then randomly sampled from a list of farm families in each village and ward. A total of 613 farm households were surveyed using a standardized survey instrument administered by trained enumerators. 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 2007/08 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.

5 Results and Discussions

5.1 Farm Household Characteristics

Table 1 provides a summary of descriptive statistics for the sampled farmers disaggregated by their adoption status of improved pigeonpea varieties. The results show that improved pigeonpea varieties were adopted by 115 households, representing 21.2% of the growers and 18.8% of the total sample. About 89% of surveyed households were male-headed, but there was a significantly higher proportion of male-headed households (93.9%) among adopters compared non-adopters (88.2). The average age of the household head was about 46.9 years, and there was no significant age difference between adopters and non-adopters. Similarly, household size, which averaged 6.1 members, did not differ significantly between the two groups. A typical household head had about 5.8 years of formal education, but heads of adopting households were slightly more educated (6.6 years) than those of non-adopting households (5.7 years), supporting the proposition that formal education is positively associated with technology adoption (FEDER et al., 1985, GEROSKI, 2000, and KASSIE et al., 2009). The size of land owned or cultivated by each household in the reference season and annual household incomes did not differ between adopting and non-adopting households, implying that the two groups were of comparable wealth status.

There were remarkable differences in access to agricultural information sources between adopting and non-adopting households. A significantly larger proportion of adopters (90.4%) had accessed government extension services in the 2007/08 season compared to non-adopters (75.5%). This could be partly explained by the fact that adopters reside at a significantly closer proximity (10.2 km) to the nearest government agricultural extension office than non-adopters (12.3 km), a finding also reported by KIBAARA et al. (2009). Ownership of information access assets was 50.4, 75.7 and 2.8% for mobile phones, radios and TV sets, respectively. However, the proportion of adopters owning mobile phones was significantly higher than that of non-adopters. This is another indication that adopters may be more exposed to agricultural information than non-adopters. Few households (18.8%) belonged to community/social groups or associations but membership to these groups was significantly higher for adopting than for non-adopting households. Participation in groups is a proxy for social capital; therefore, this finding is consistent with the notion that social capital is positively associated with technology adoption (SAKA and LAWAL, 2009). Access to credit was very low (5.5%) and this did not differ significantly between adopters and non-adopters.

Table 1. Household characteristics by adoption status of improved pigeonpea in 2007/08

Characteristic	Non-adopters (N=498)	Adopters (N=115)	Total (N=613)	Difference
Socio-demographic factors				
Proportion of male-headed households (%)	88.2	93.9	89.2	-5.8**
Age of the household head (years)	47	46	46.9	1.0
Education level of the household head (years)	5.7	6.6	5.8	-0.97***
Household size (total number of members)	6.1	6.2	6.1	-0.1
Total cultivated land (ha)	2.01	1.93	2.2	0.3
Total household annual income from all sources (Tsh Million)	5.18	4.10	4.98	1.10
Information access and institutional factors				
Participation in participatory variety selection (PVS)	5.02	24.34	8.02	-19.32**
Distance to the nearest agricultural office (km)	12.3	10.2	11.9	2.11***
Distance to the main market (km)	7.27	7.67	7.35	-0.39
Number of years of residence in the village	36.01	36.84	36.68	0.82
Contact with government extension agent (% households)	75.5	90.4	78.3	-13.9***
Participation in technology transfer (% households)	11.5	33.0	15.7	-21.6***
Own mobile phone (% of households)	47.8	61.7	50.4	-13.9***
Own mobile radio (% of households)	73.9	83.5	75.7	-9.6**
Own mobile TV (% of households)	2.6	3.5	2.8	-0.9
Got some credit (% households)	5.0	7.8	5.5	-2.8
Membership to farmer/community group (% households)	17.1	26.1	18.8	-9.0**
Number of groups the household belongs to	1.2	1.1	1.2	0.09
Household received some credit (% households)	5.0	7.8	5.5	-2.8

*, ** and *** indicate that difference between adopters and non-adopters is statistically significant at 10, 5 and 1% level, respectively (t-tests are used for differences in means).

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

5.2 Patterns of Improved Pigeonpea Diffusion and Adoption

Exposure to improved pigeonpea varieties among the interviewed households was generally low (table 2). Results show that just about one third of the households had some knowledge about the improved varieties. Amongst the improved varieties, ICEAP 00040 was the most widely known (30%) followed by ICEAP 00053, known only by 5.1% of the surveyed farmers. The rest of the varieties (ICEAP 00020, ICEAP 00068) are each known by less than 2% of the sample.

A number of respondents who expressed awareness of the improved varieties have never grown them. For instance, although 30% of the farmers expressed some knowledge of the long duration variety ICEAP 00040, only 21% had ever grown it, and 16.8% actually grew it in the 2007/08 season. More generally, about 33% of the sample knew at least one improved variety, but only 23% have ever grown an improved variety. In the 2007/08 season, just a mere 18.8% of the sample grew at least one improved variety. Overall, these results show there is a gap in knowledge of improved pigeonpea varieties, which presents an opportunity for ICRISAT to disseminate the information to farmers in potential pigeonpea growing areas.

Table 2. Exposure, diffusion and adoption of Improved pigeonpea varieties in the study area

Characteristic	Kondoa	Karatu	Babati	Arumeru	Total
Exposed to variety					
ICEAP 00040	1.3	24.0	41.7	52.9	30.0
ICEAP 00053	1.9	0.7	12.8	5.2	5.2
ICEAP 00020	—	0.7	7.1	5.2	3.3
ICEAP 00068	—	—	1.3	—	0.3
<i>At least one improved variety</i>	3.2	24.7	48.7	54.2	32.8
Ever adopted variety					
ICEAP 00040	1.3	23.3	27.6	32.0	21.0
ICEAP 00053	0.0	0.7	8.3	0.7	2.4
ICEAP 00020	—	—	0.6	0.7	0.3
ICEAP 00068	—	—	1.3	—	0.3
<i>At least one improved variety</i>	1.3	24.0	32.7	33.3	22.8
Adopted variety in 2007/08 season					
ICEAP 00040	1.3	21.3	25.6	30.1	16.8
ICEAP 00053	—	—	—	0.7	0.2
ICEAP 00020	—	0.7	5.8	1.3	2.0
ICEAP 00068	—	—	1.3	—	0.3
<i>At least one improved variety</i>	1.3	22.0	30.1	31.4	18.8

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

Exposure to and adoption of improved pigeonpea varieties varied significantly across the study districts, as shown in table 2. More generally, Arumeru District recorded the highest exposure to improved varieties at 54.2%, followed by Babati (48.7%), Karatu (24.7%) and Kondoa (3.2%). Similarly, the proportion of surveyed farmers who adopted an improved variety in the 2007/08 season was highest in Arumeru District (31.4%), followed by Babati, Karatu and Kondoa, with adoption rates of 30.1, 22, and

1.3%, respectively. These results appear to suggest that a spirited campaign by ICRISAT and partners is required to promote improved varieties, particularly, in Kondoa and Karatu, where more than three quarters of the farmers have not yet been exposed to any of the improved varieties. Further, since improved varieties are unknown to about 67% of the sample, there is need to promote the varieties in all districts.

As discussed above, these sample adoption rates are low because they have substantial non-exposure bias resulting from the very low diffusion rates of improved pigeonpea varieties. Thus, sample adoption rates are biased downwards because they include farmers who were not yet exposed to the varieties and, therefore, they cannot adopt unless they are exposed. In fact some farmers would have adopted the improved pigeonpea varieties if they had been exposed.

Because the non-exposure bias is caused by the inclusion in the computation of the adoption rate of non-adopting farmers who might have adopted improved varieties if they knew about them, one would think that an obvious fix to this non-exposure bias is to take the adoption rates among farmers exposed to improved pigeonpea as better estimates of their adoption rates. This appears more appealing in terms explaining the potential adoption rates because it somehow addresses the problem of non-exposure bias. As shown in table 3, adoption rates of improved varieties among the sub-sample of farmers that were aware of the improved varieties were significantly 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 2007/08 season was 55.9% compared to a lower adoption rate of 18.8% for the whole sample.

Table 3. Comparison of adoption rates between the entire sample and exposed sub-sample

Characteristic	% of entire sample	% of the exposed sample
Ever adopted variety		
ICEAP 00040	21.0	70.1
ICEAP 00053	2.4	46.9
ICEAP 00020	0.3	10
ICEAP 00068	0.3	100.0
<i>At least one improved variety</i>	22.8	69.7
Adopted variety in 2007/08 season		
ICEAP 00040	16.8	54.9
ICEAP 00053	2.0	38.8
ICEAP 00020	0.2	—
ICEAP 00068	0.3	50
<i>At least one improved variety</i>	18.8	55.9

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

However, as earlier discussed the sample adoption rate among the exposed is likely to significantly overestimate the true population adoption rate. The reason for this is a positive population selection bias by which the subpopulation most likely to adopt gets exposed first. As expressed by DIAGNE (2006), the positive selection bias arises from two sources. The first source is the farmers' self-selection into exposure, reflecting the fact that exposure is partly a farmer's choice. For example, a farmer who is actively searching for varieties that could potentially do better than the ones he/she possesses is more likely to be exposed to new varieties including improved pigeonpea. The second source of the selection bias results from the fact that some farmers (the so-called progressive farmers, in particular) and communities are targeted by research and extension people. It is most likely that the farmers that have been targeted for exposure to a variety are precisely those who are more likely to adopt it. Hence, the adoption rate in the targeted subpopulation is most likely to overestimate the true population adoption rate. In the subsequent next sections we use the counterfactual setting framework to obtain a consistent ATE-based estimate of the population adoption rates of improved pigeonpea and their determinants.

5.3 Determinants of Knowledge of Improved Varieties of Pigeonpea

In this study, about 33% 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 at least one improved variety of pigeonpea (table 4). Results indicate that several variables have statistically significant coefficients at 5% level. All variables capturing access to extension information (number of contacts with extension workers participation in Participatory Variety Selection (PVS) and distance to the agricultural office) returned significant coefficients with expected positive signs at 1% level suggesting that farmers that participated in PVS activities through which improved pigeonpea varieties are usually introduced by extension workers and those with more contacts with extension personnel are significantly more likely to know of the existence of improved pigeonpea varieties than farmers that did not participate in PVS activities and those that had less contacts with extension personnel. The distance to the agricultural office, returned a significant and negative coefficient. The finding highlights the significant role of extension services in creating the awareness about available improved pigeonpea varieties. Most pigeonpea varieties are first disseminated through field days and participatory variety selection, and government extension workers play an important role in such activities hence it is not surprising that proximity to government extension offices increases the propensity to be aware of improved technologies of pigeonpea. The findings also provide evidence of the effectiveness of PVS and extension activities and provide justification for the scaling up PVS activities and dissemination efforts through extension.

The variable capturing access to markets (the distance to the nearest main market) returned a negative and expected sign and it was significant at 10% level suggesting that households far away from markets have a lower propensity to access information about improved varieties.

The coefficient of the education level of a household is positive and significant at 10% level suggesting that households headed by more educated people have a higher propensity to get exposed to improved varieties than those with less education. District dummies for Kondoa and Karatu returned negative and significant coefficients at 1% level suggesting that households in the two districts have significantly lower propensity to get exposed to new pigeonpea varieties than household from the reference district, Arumeru.

The coefficients for variables such as the age and gender of the household-head, land holding size, ownership of assets used for information access such as radio and television are not significant suggesting that they are irrelevant in explaining the difference of rates of awareness of improved pigeonpea among households.

Table 4. Determinants of the Probability of Exposure to Improved Pigeonpea in Tanzania

Variables	Coef.	Std. Err.	Z	P> z
Number of contact with extension workers	0.1271***	0.0488	2.6	0.009
Participation in participatory variety selection (PVS)	1.0880***	0.2236	4.86	0
Household size	0.0358	0.0318	1.13	0.261
Gender of head (1=Male, 0=Otherwise)	0.0107	0.1981	0.05	0.957
Distance to the main market (km)	-0.0256*	0.0138	-1.86	0.064
Distance to an agricultural office (km)	-0.0410***	0.0079	-5.2	0
Ownership of ICT materials(cell phone, radio, television) (1=yes,0= otherwise)	-0.0395	0.1833	-0.22	0.829
Education of head of household (yrs)	0.0486*	0.0261	1.86	0.063
Age of head (yrs)	0.0232	0.0273	0.85	0.395
The square of age	-0.0002	0.0003	-0.64	0.521
Kondoa	-2.0919***	0.2287	-9.15	0
Karatu	-0.9492***	0.1767	-5.37	0
Babati	0.0326	0.1737	0.19	0.851
Constant	-0.4617	0.7461	-0.62	0.536
Number of interviews	607			
Pseudo R ²	0.2655			
LR Chi ²	205.80***			

Key : * p<0.10; ** p<0.05; *** p<0.01

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

5.5 Rate and Determinants of Adoption of the Improved Pigeonpea Technologies

Adoption Rates for Improved Pigeonpea

Table 5 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 2008. 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.

Table 5. Adoption rates and adoption gap of the improved technology in 2008

Estimator	Parameter	Std. Err.	Z	P> z
Proportion of exposed households	0.332784	0.019142	17.39	0
ATE (potential adoption rate)	0.6153	0.0447	13.74	0
ATE1 (adoption rate among exposed sample)	0.5661	0.0268	21.11	0
ATE0 (adoption rate among non-exposed)	0.6383	0.0598	10.67	0
Joint exposure and adoption rate (JEA)	0.1884	0.0089	21.11	0
Adoption gap (GAP=ATE-JEA)	-0.4259	0.0399	-10.67	0
Population Selection Bias (PSB)	-0.0482	0.0355	-1.36	0.175

Key: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

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

The diffusion results show that only 33% of farm households were aware of at least one improved pigeonpea variety in 2008. This incomplete diffusion of the improved pigeonpea varieties restricted the actual adoption (JEA) rate of at least one improved variety to about 19%, whereas the potential adoption rate (ATE) was 62% in the same year. This implies that the improved pigeonpea adoption rate in Tanzania could have been 62% in 2008 if the whole population had been exposed to improved varieties of pigeonpea, instead of the joint exposure and adoption rate of 19%. Thus, when compared to the sample adoption rate of 43%, there is a substantial population adoption gap of 43% 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 43% 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, 57% 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 64%. 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 5% 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.

Determinants of Adoption of Improved Pigeonpea Varieties

Results on the determinants of improved pigeonpea adoption for the ATE probit model are presented in table 6. Results show that factors such as the distance to agricultural office, the land holding size and the ownership of livestock have a significant effect on the adoption of improved pigeonpea varieties.

The households in the second quartile of the land holding size returned a positive and significant coefficient at 10% level suggesting that farmers in this quartile of land holdings have a higher propensity to cultivate improved pigeonpea varieties than those in the reference category (fourth quartile). Stated the other way, the finding suggests that households with smaller holding have a higher propensity to adopt improved varieties of pigeonpea. The finding is consistent with findings by CONELLY (1993) who reports that when farmers are faced with land pressure in the Philippines, they are forced to intensify their agricultural production and resource-use efficiency through the adoption of improved irrigation technologies. In our case, farmers facing land pressure have the incentive to intensify through the cultivation of improved pigeonpea varieties which also provides them the opportunity to get higher returns once the crop is sold.

On the other hand, access to pigeonpea seed is positively associated with adoption. This implies that policy interventions that make improved pigeonpea seeds available to more farmers could facilitate adoption. The very limited numbers of private seed enterprises and the low attention accorded to the informal seed sector narrowed the options available to farmers for obtaining modern varieties at affordable prices at the right place and time. The private sector lacks the incentive to participate in the enhanced delivery of seeds of these crops as the size of the market is small and farmers are able to use saved and recycled seed for 3-5 years.

Table 6. Determinants of adoption of improved pigeonpea-ATE probit model

Variables	Coef.	Std. Err.	Z	P>z
Number of contact with extension workers	-0.0666	0.1021	-0.65	0.514
Participation in participatory variety selection (PVS)	0.1909	0.2909	0.66	0.512
Household size	0.0710	0.0698	1.02	0.309
1 st quartile of land size	0.4265	0.3689	1.16	0.248
2 nd quartile of land size	0.5612*	0.3049	1.84	0.066
3 rd quartile of land size	0.2969	0.3262	0.91	0.363
Gender of head (1=Male, 0=Otherwise)	0.4499	0.3513	1.28	0.2
Distance to the main market (km)	0.0128	0.0247	0.52	0.605
Distance to an agricultural office (km)	-0.0173	0.0166	-1.04	0.297
Access to pigeonpea seed (1=yes,0= otherwise)	1.8026***	0.2628	6.86	0
Ownership of ICT materials(cell phone, radio, television) (1=yes,0= otherwise)	0.3679	0.3535	1.04	0.298
Education of head of household (yrs)	0.0112	0.0550	0.2	0.838
Age of head (yrs)	-0.0002	0.0506	0	0.998
The square of age	0.0000	0.0005	-0.06	0.954
Access to credit (1=yes,0= otherwise)	-3.6907	2.7819	-1.33	0.185
Interaction for education and credit access	0.1613	0.2172	0.74	0.458
Interaction for age and credit access	0.0596	0.0381	1.56	0.118
Total Livestock Units	0.0529*	0.0278	1.9	0.057
Kondoa	-0.4768	0.4709	-1.01	0.311
Karatu	-0.0829	0.3402	-0.24	0.807
Babati	-0.3558	0.3066	-1.16	0.246
_Constant	-0.6218	1.4300	-0.43	0.664
Number of interviews	202			
Pseudo R2	0.313			
Wald Chi 2	69.76			

Key: * p<0.10; ** p<0.05; *** p<0.01

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

The ownership of livestock returned a positive and significant coefficient suggesting that households that own larger amounts of livestock have a higher propensity to adopt improved varieties of pigeonpea than those that do not own livestock. In this study, the ownership of livestock is an indicator of the wealth of the household, suggesting that slightly wealthier households have the means to access and use improved pigeonpea technologies. In general one constraint to pigeonpea cultivation is the lack of seed. The positive coefficient for livestock 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 main market), education, age and gender of the head of household were not significant. The coefficient for the size of the household is not significant implying that labour is not a constraint for Tanzanian farmers to adopt improved 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 Tanzania. We find that only 33% of the farmers are aware of the improved varieties of pigeonpea. The incomplete awareness of the varieties by the farming population has restricted adoption rates of improved varieties to 19%. The adoption rates could be up to 62% in 2008 instead of the observed sample adoption rate of 19% if the whole farming population was exposed to the improved pigeonpea varieties by the year 2008. This has led to the adoption gap of about 43%, suggesting that there is potential for increasing the adoption rate of improved pigeonpea by 43% if its diffusion to the population can be completed.

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. The awareness of improved varieties is mainly accelerated by participation in PVS activities and proximity to agricultural offices, which suggests that there is potential for increasing the diffusion of the new varieties through 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. Signifying the presence of seed and economics constraints, the study has shown that the propensity of cultivating (adopting) at least one improved pigeonpea variety is high among farmers that are wealthier with a larger number of livestock units and those with access to seed.

References

- ASHBY, J.A. and L. SPERLING (1995): Institutionalizing participatory, client driven research and technology development in agriculture. In: *Development and Change* 26 (4): 753-770.
- BANDIERA, O. and I. RASUL (2006): Social Networks and Technology Adoption in Northern Mozambique. In: *The Economic Journal* 116: 869-902.

- BESLEY, T. and A. CASE (1993): Modeling technology adoption in developing countries. In: *The American Economic Review* 83 (2). Papers and Proceedings of the 105 Annual Meeting of the American Economic Association, Anaheim, California: 396-402.
- BLUNDELL, R. and M. COSTA DIAS (2000): Evaluation Methods for Non-Experimental Data. In: *Fiscal Studies* 21 (4): 427-468.
- CONELLY, W.T. (1993): Agricultural intensification in a Philippine frontier community: Impact on labor efficiency and farm diversity. In: *Human Ecology* 20 (2): 203-223.
- DIAGNE, A. (2006): Diffusion and adoption of NERICA rice varieties in Côte d'Ivoire. In: *The Developing Economies XLIV-2* (2006) (44): 208-231.
- DIAGNE, A. and M. DEMONT (2007): Taking a New look at Empirical Models of Adoption: Average Treatment Effect estimation of Adoption rate and its Determinants. In: *Agricultural Economics* 37 (2007) (2-3): 201-210.
- DIMARA, E. and D. SKURAS (2003): Adoption of agricultural innovations as a two-stage partial observability process. In: *Agricultural Economics* 28 (1): 187-196.
- FAOSTAT (2010): Online agricultural statistics. URL: <http://www.faostat.org>.
- FEDER, G., R.E. JUST and D. ZILBERMAN (1985): Adoption of Agricultural Innovations in Developing Countries: A Survey. In: *Economic Development and Cultural Change* 33 (2): 255-298.
- FOSTER, A and M. ROSENZWEIG (1995): Learning by Doing and Learning from Others: Human Capital and Farm household Change in Agriculture. In: *Journal of Political Economy* 103 (6): 1176-1209
- GEROSKI, P.A. (2000): Models of technology diffusion. In: *Research Policy* 29 (4): 603-625.
- JOSHI, P.K., P. PARTHASARATHY RAO, C.L.L. GOWDA, R.B. JONES, S.N. Silim, K.B. SAXENA and J. KUMAR (2001): The world chickpea and pigeonpea economies: facts, trends, and outlook. International Crops Research Institute for the Semi-Arid Tropics, Patancheru, Andhra Pradesh, India.
- KASSIE, M., P. ZIKHALI, K. MANJUR and S. EDWARDS (2009): Adoption of Organic Farming Techniques: Evidence from a Semi-Arid Region of Ethiopia. Environment for Development, Discussion Paper Series 09-01, Washington, D.C.
- KIBAARA, B., J. ARIGA, J. OLWANDE and T.S. JAYNE (2009): Trends in Kenyan Agricultural Productivity: 1997-2007. Working Paper 31/2008. Tegemeo Institute of Agricultural Policy and Development, Nairobi, Kenya.
- KIMANI, P.M. (2001): Pigeonpea Breeding: Objectives, Experiences, and Strategies for Eastern Africa. In: Silim, S.N., G. Mergeai and P.M. Kimani (eds.) (2001): Status and potential of pigeonpea in Eastern and Southern Africa: proceedings of a regional workshop, 12-15 Sep 2000, Nairobi, Kenya. Gembloux Agricultural University; Gembloux, Belgium, and International Crops Research Institute for the Semi-Arid Tropics, Patancheru, Andhra Pradesh, India.
- KOUNDOURI P., C. NAUGES and V. TZOUVELEKAS (2006): Technology adoption under production uncertainty: theory and application to irrigation technology. In: *American Journal of Agricultural Economics* 88 (3): 657-670.

- MERGEAL, G., P. KIMANI, A. MWANG'OMBE, F. OLUBAYO, C. SMITH, P. AUDI, J.P. BAUDOIN, and A. LE ROI (2001): Survey of pigeonpea production systems, utilization and marketing in semi-arid lands of Kenya. In: *Biotechnology, Agronomy, Society and Environment* 5 (3): 145-153.
- MOFFIT, R. (1991): Program Evaluation with Nonexperimental Data. In: *Evaluation Review* 15 (3): 291-314.
- ROGERS, E. (1995): *Diffusion of innovations*. Fourth edition. The Free Press, New York, NY.
- ROSENBAUM, P.R. and D.B. RUBIN (1983): The Central Role of the Propensity Score in Observational Studies for Causal Effects. In: *Biometrika* 70 (2): 41-55.
- RUBIN, D. (1974): Estimating Causal Effects of Treatments in Randomized and non-randomized Studies. In: *Journal of Educational Psychology* 66: 688-701.
- SAHA, L., L.H. ALAN and S. ROBERT (1994): Adoption of emerging technologies under output uncertainty. In: *American Journal of Agricultural Economics* 76 (4): 836-846.
- SAKA, J.O. and B.O. Lawal (2009): Determinants of Adoption and Productivity of Improved Rice Varieties in Southwestern Nigeria. In: *African Journal of Biotechnology* 8 (19): 4923-4932.
- SAXENA, K.B. (2008): Genetic Improvement of Pigeon Pea – A Review. In: *Tropical Plant Biology* 1 (2): 159-178.
- SHIFERAW, B., J. OKELLO, G. MURICHO, J. OMITI, S. SILIM and R. JONES (2008): *Unlocking the Potential of High-Value Legumes in the Semi-Arid Regions: Analyses of the Pigeonpea Value Chains in Kenya*. Research Report No. 1: Institutions, Markets, Policy Impacts. International Crops Research Institute for the Semi-Arid Tropics, Nairobi, Kenya.
- SHIFERAW B., S. SILIM, G. MURICHO, P. AUDI, J. MLIGO, S. LYIMO, L. YOU and J.L. CHRISTIANSEN (2005): *Assessment of the Adoption and Impact of Improved Pigeonpea Varieties in Tanzania*. Working Paper Series no. 21: Socioeconomics and Policy. International Crops Research Institute for the Semi-Arid Tropics, Patancheru, India.
- WOOLDRIGE, J. (2002): *Econometric analysis of cross section and panel data*. The MIT Press, Cambridge, Massachusetts, USA.

Contact author:

Franklin Simtowe

International Crops Research Institute for the Semi-Arid Tropics (ICRISAT),

Regional Office for Eastern and Southern Africa

United Nations Avenue, World Agroforestry Centre, Gigiri P.O.Box 39063-00623, Nairobi, Kenya

e-mail: f.p.simtowe@cgiar.org