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Heterogeneous information exposure and technology adoption: the case of tissue culture bananas in Kenya

Nassul Ssentamu Kabunga[a,*], Thomas Dubois[b], Matin Qaim[c]

[a]*International Food Policy Research Institute (IFPRI), Plot 15, East Naguru Road, P.O. Box 28565, Kampala, Uganda*
[b]*International Institute of Tropical Agriculture (IITA), P.O. Box 7878, Kampala, Uganda*
[c]*Department of Agricultural Economics and Rural Development, Georg-August-University of Goettingen, 37073 Goettingen, Germany*

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Abstract

Classical innovation adoption models implicitly assume homogenous information flow across farmers, which is often not realistic. As a result, selection bias in adoption parameters may occur. We focus on tissue culture (TC) banana technology that was introduced in Kenya more than 10 years ago. Up till now, adoption rates have remained relatively low. We employ the average treatment effects approach to account for selection bias and extend it by explicitly differentiating between awareness exposure (having heard of a technology) and knowledge exposure (understanding the attributes of a technology). Using a sample of Kenyan banana farmers, we find that estimated adoption parameters differ little when comparing the classical adoption model with one that corrects for heterogeneous awareness exposure. However, parameters differ considerably when accounting for heterogeneous knowledge exposure. This is plausible: while many farmers have heard about TC technology, its successful use requires notable changes in cultivation practices, and proper understanding is not yet very widespread. These results are also important for other technologies that are knowledge-intensive and require considerable adjustments in traditional practices.

JEL classification: C8, D8, O3, Q12, Q16, Q18

Keywords: Technology adoption; adoption gap; biotechnology; average treatment effects; heterogeneous knowledge exposure; Kenya

1. Introduction

Innovation adoption in agriculture has been widely studied (Feder et al., 1985; Sunding and Zilberman, 2001). Still, many questions related to social and institutional environments, as well as to the dynamics of the adoption process, remain unanswered (Doss, 2006). The extent and speed by which available innovations are disseminated and adopted determine the scale of their effect on the target population. Not all potential adopters will start using a technology when it appears on the market; rather adoption typically follows a certain time path that can partly be explained through the existence of information disequilibria (Feder et al., 1985; Geroski, 2000). Most empirical studies have neglected the role of information and only concentrated on the personal and structural differences to explain technology adoption behavior. These studies usually employ standard probit or logit models. Yet the theoretical base of this classical approach is narrow, as it implicitly assumes a homogenous population of potential adopters and no active information search (Geroski, 2000; Karshenas and Stoneman, 1995). When a technology is new and not widely known, there will likely be selection problems, because every individual in the population will not have equal chances to be exposed and consequently adopt.

While previous research has indentified this problem, it has hardly been addressed through proper econometric techniques. One exception is Diagne and Demont (2007) who proposed the use of the average treatment effects (ATE) framework, which is common in the modern impact evaluation literature (Imbens and Wooldridge, 2009) but has not been widely applied in adoption studies. The ATE framework foresees two stages to estimate unbiased adoption parameters, the first that models heterogeneous information flow within the population as a function of

*Corresponding author. Tel.: +256-414-285-060.
E-mail address: n.kabunga@cgiar.org (N.S. Kabunga)

Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article. Please note: Wiley-Blackwell, Inc. is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

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individual characteristics, and the second that models actual adoption controlling for nonrandom selection (Diagne and Demont, 2007).

Diagne and Demont (2007) used the ATE framework to explain the adoption of new rice varieties in Côte d'Ivoire, differentiating between those aware and unaware of the new varieties. Being aware of a new technology is a necessary condition for adoption, but it may not in all cases suffice for knowing how to use the technology successfully. Especially for knowledge-intensive technologies, which often require substantial changes in traditional cultivation practices, information exposure may be more complex. We extend the approach by Diagne and Demont (2007) by explicitly accounting for different levels of information exposure. In particular, we differentiate between awareness exposure and knowledge exposure. In this context, awareness exposure means that a farmer has heard about a technology, whereas knowledge exposure implies that he/she has acquired more profound information about the technology's attributes and performance. The latter is particularly important among peasant farmers in developing countries with limited capacity to take risk. As new technologies are often perceived riskier, they may not be widely adopted if not properly understood. Moreover, knowledge acquisition requires active communication and learning, so that selection bias caused by knowledge differences is likely to be higher than bias caused by awareness differences.

We focus on the adoption of tissue culture (TC) bananas in Kenya. Traditionally, bananas in East Africa are propagated by suckers taken from old plantations. While this is a cheap way of establishing a new plantation, the main problem is that pests and diseases are also multiplied. TC plantlets, which are produced in the laboratory, are more expensive but pathogen-free. Thus, TC plantations can establish faster, yield higher, and have more uniform production (Eckstein and Robinson, 1995; Vuylsteke and Ortiz, 1996). However, apart from the higher cost for the planting material, the full potential of TC bananas can only be realized with higher input intensities and proper plantation management (Dubois et al., 2006). For typical banana farmers in Kenya, this implies a notable change in cultivation practices (Qaim, 2000).

These characteristics make TC bananas an interesting example to study the role of heterogeneous information flow. The technology was introduced in Kenya more than 10 years ago, but adoption has remained relatively low. Using a sample of 385 banana-growing households, we estimate TC adoption parameters at individual and population levels, controlling for both awareness and knowledge exposure bias. Furthermore, we estimate and explain the adoption gap caused by information exposure differences.

2. Background

In East Africa, banana is almost exclusively grown by smallholder farmers for home consumption or local markets. While the trend has changed more recently, crops like banana were traditionally considered 'subsistence' and had received low priority in national agricultural research policy since colonial times (Maredia et al., 2000). As a result, banana yields have experienced accelerated declines since the 1970s, mainly due to pests and diseases, soil nutrient depletion, and poor crop management (Gold et al., 1998; Komarek and Ahmadi-Esfahani, 2011). To safeguard banana production and productivity, access to improved pest- and disease-free planting material is considered fundamental. However, as triploids, bananas are genetically sterile, so that classical breeding for resistance is extremely difficult (Ortiz et al., 1995). Moreover, the traditional method of uprooting suckers from old plantations and using them as planting material for new ones fosters the transfer of pests and diseases, thus reducing yield and plantation longevity.

With the advent of modern biotechnology, TC techniques can be used to produce clean and pathogen-free plantlets of banana and other vegetatively propagated crops in the laboratory. Compared with traditional banana suckers, TC also allows for mass production of uniform planting material in relatively short periods of time, ensuring all-year round availability, an aspect especially vital for commercial farming. Under optimum crop husbandry, TC plantlets establish faster, grow more vigorously, have a shorter and more uniform production cycle, and yield higher (Eckstein and Robinson, 1995). However, especially during the early growth stages, TC bananas need extra care and attention, which is against the frequently observed tradition among smallholders to consider banana as a security crop that provides some food and income even without any inputs. While TC bananas have been widely adopted in most commercial banana-producing regions of the world (Vuylsteke and Ortiz, 1996), their use in East Africa is still fairly limited. But there have been different efforts to change this situation.

In Kenya, the potential benefits stimulated national and international organizations to boost research into the use and dissemination of TC banana plantlets, with the hope to increase the sector's productivity and profitability. The International Service for the Acquisition of Agri-biotech Applications (ISAAA) had started a project in the late-1990s, producing and disseminating TC plantlets to local banana farmers (Qaim, 2000; Wambugu and Kiome, 2001). Later on, the Kenya Agricultural Research Institute (KARI) and Jomo Kenyatta University of Agriculture and Technology (JKUAT) also became involved in TC bananas.

Since 2003, Africa Harvest, an international nongovernmental organization (NGO), has promoted more widespread TC adoption, using innovative models of technology delivery and a whole value chain approach. Whereas KARI and JKUAT have spun off laboratories and set up farmer group-managed TC banana nurseries in several parts of the country, Africa Harvest collaborates with private companies to provide subsidized TC plantlets to farmers who are organized in groups. Africa Harvest does not operate own TC nurseries, but farmers collect plantlets at agreed collection centers in various locations. To augment dissemination activities, selected early adopters were facilitated to establish demonstration plots and act as product champions within their farmer group and beyond. Considering Kenya as a whole, only around 6% of all banana farmers have adopted TC so far, although in Central and Eastern Provinces, where most of the dissemination programs started, adoption rates are already higher (Njuguna et al., 2010).

3. Analytical framework

Beside analyzing the adoption decision itself, an important question in our context is whether every potential adopter is informed about the technology's existence and its performance attributes. In fact, individual adoption decisions heavily depend on the information personally acquired about the technology in question. Such information may be obtained by observing and interacting with other adopters, talking to technology suppliers, or experimenting with the technology in a stepwise manner (Baerenklau, 2005). We analyze TC banana adoption in Kenya, controlling for heterogeneous information exposure.[1]

In nonuniform exposure situations, observed sample adoption estimates may inconsistently represent true population adoption parameters. In other words, classical approaches to analyze adoption (e.g., standard probit or logit models) may yield biased estimates even if using a random sample. The reason is that farmers self-select into exposure, while researchers and extension workers have a tendency to target progressive farmers first (Diagne, 2006). To account for selection bias, some authors employed a latent variable correction procedure (e.g., Besley and Case, 1993; Foltz and Chang, 2002; Dimara and Skuras, 2003; Saha et al., 1994). However, this approach was criticized by Diagne and Demont (2007) who argued that the parametric latent variable formulation is not efficient since the adoption outcome variable is binary, rendering the resulting estimates "messy" (cf. Wooldridge, 2002).

More importantly, Diagne and Demont (2007) showed that the explicit and implicit functional forms and distributional assumptions used in parametric selectivity bias correction models are not enough to identify and estimate the potential adoption rate and adoption functions for the full population. Instead, they suggested the use of the counterfactual ATE framework, which allows both nonparametric and parametric methods to derive consistent estimates. Based on original work by Rubin (1973), the ATE framework is today widely used in program evaluation. The ATE parameter measures the effect of treatment on a person randomly selected in the population (Imbens and Wooldridge, 2009). In the adoption context, treatment corresponds to exposure to a technology, and the ATE measures the population mean adoption outcome when all population members have been exposed.

[1] As outlined above, in our empirical approach we differentiate between two different levels of exposure, namely awareness exposure and knowledge exposure. However, for explaining how the procedure works in theory, the level of exposure does not matter, so that we refer to exposure more generally in the following paragraphs.

In the ATE framework, the main element is the notion of potential outcomes. It is assumed that some farmers get exposed while others do not. For observations in N households, we can denote a binary variable w to indicate the observed status of exposure, with $w = 1$ if the farmer is exposed to TC banana technology (treated), and $w = 0$ if the farmer is nonexposed (control). Thus, out of N households we shall have N_e as the number of exposed. For each household, we also observe a k-dimensional column vector of covariates x. At the individual level, we want to explain the adoption status (binary), while at the population level, we want to explain exposure rates (N_e/N), adoption rates (N_a/N) assuming universal exposure, and adoption rates among the exposed (N_a/N_e) in cases of incomplete exposure.

Following the notation in Diagne and Demont (2007), we use y as an indicator variable for the potential adoption outcome, where y_1 is the outcome with and y_0 without exposure

$$y = wy_1 = y_0(1-w) + y_1 w = \begin{cases} y_0 & \text{if } w = 0, \\ y_1 & \text{if } w = 1. \end{cases} \tag{1}$$

Hence, under incomplete exposure, the treatment effect for farmer i is measured by the difference $(y_{1i} - y_{0i})$, or aggregated to the population level as $E(y_1 - y_0)$. In principle, this is the ATE of exposure. Unfortunately, we cannot observe the outcome with and without exposure for the same farmer, so that it is impossible to measure $(y_{1i} - y_{0i})$. However, since exposure is a necessary precondition for adoption, y_0, will always be zero. Thus, the adoption impact of any farmer is given by y_{1i}, and the mean adoption impact of exposure is reduced to $E(y_1)$. For the exposed subsample ($w = 1$), the mean adoption impact on the exposed subpopulation is given by the conditional expected value $E(y_1 \mid w = 1)$, which is the ATE on the treated (ATE_1). Similarly, for the nonexposed subsample ($w = 0$), the mean adoption impact is given by $E(y_0 \mid w = 0)$, which is the ATE on the untreated (ATE_0).

From Eq. (1), it can further be seen that with $y_0 = 0$ the expression of the observed adoption outcome reduces to $y = wy_1$, implying that the observed adoption outcome variable combines exposure and adoption outcome. This is referred to as the population mean joint exposure and adoption parameter (JEA) (Diagne and Demont, 2007). While ATE measures the potential demand for the technology by the population, JEA measures the population mean observed adoption outcome. The difference between the JEA and ATE is the population adoption gap, $GAP = E(y) - E(y_1)$, which is strictly negative and diminishing with increasing exposure. It exists due to partial exposure and measures the unmet population demand for the technology. The difference between mean potential adoption outcome in the exposed subpopulation and mean potential adoption outcome in the full population is the population selection bias, $PSB = ATE_1 - ATE = E(y_1 \mid w = 1) - E(y_1)$.

For consistent estimation of population adoption parameters, we identify ATE based on the conditional independence (CI) assumption involving potential outcomes (Imbens and

Wooldridge, 2009; Wooldridge, 2002). The CI assumption postulates that a set of observed covariates determining exposure, when controlled for, renders the treatment status w independent of the potential outcomes y_1 and y_0.

Based on the CI assumption, ATE parameters can be estimated either with parametric or nonparametric regression methods. We estimate ATE, ATE_1, and ATE_0 with parametric procedures by specifying a model for the conditional expectation of the observed variables y, x, and w (for details see Diagne and Demont, 2007):

$$E(y \mid x, w = 1) = g(x, \beta), \tag{2}$$

where g is a known function of the vector of covariates determining adoption, x, and β is the unknown parameter vector which can be estimated by maximum likelihood procedures using observations (y, x) from the exposed subsample with y as the dependent variable. With the estimated parameters $\hat{\beta}$, the predicted values are computed for all observations in the sample, including the nonexposed. The average of these predicted values, $g(x, \hat{\beta})$, is used to compute ATE for the full sample, and ATE_1 and ATE_0 for the exposed and nonexposed subsamples, respectively

$$\widehat{ATE} = \frac{1}{N} \sum g(x, \hat{\beta}) \tag{3}$$

$$\widehat{ATE}_1 = \frac{1}{N_e} \sum w g(x, \hat{\beta}) \tag{4}$$

$$\widehat{ATE}_0 = \frac{1}{N - N_e} \sum (w - 1) g(x, \hat{\beta}). \tag{5}$$

Because exposure is not random, the methodology involves controlling appropriately for exposure status using a set of covariates. This first stage, which explains the factors influencing exposure, is estimated before the second-stage adoption model, whereby the covariates are allowed to differ. This makes sense, because the factors that influence information exposure are not necessarily exactly the same as those that explain adoption once exposed.

Unlike Diagne and Demont (2007) who in their empirical analysis only considered whether farmers are aware of the new technology's existence, we differentiate between two different exposure levels, namely awareness exposure and knowledge exposure. We estimate the models separately for both exposure levels and compare the results with those from a classical probit adoption model that does not control for exposure bias.

4. Data and descriptive statistics

4.1. Survey design

Although banana is grown in most parts of Kenya, this study focuses on Central and Eastern Provinces, because these are the regions where most of the TC banana dissemination activities are located. An interview-based survey of banana farmers was carried out in the second half of 2009. Within Central and Eastern Provinces, the districts of Meru, Embu, Kirinyaga, Kiambu, Murang'a, and Thika were selected based on information on the distribution of TC plantlets provided by different organizations. Furthermore, agro-ecological factors were taken into account, as these can matter much for banana yield potentials, problems with pests and diseases, and the expected advantages of TC technology (Frison et al., 1998). Based on climate data, altitude, and information about soil conditions, we differentiate between high-potential and low-potential areas. High-potential areas include the districts of Embu, Meru, and the northern half of Kirinyaga (Ndia and Gichugu Divisions), which are mainly located on the slopes of Mount Kenya. In contrast to low-potential areas, high-potential areas receive relatively high rainfall and have fertile volcanic soils; due to somewhat higher altitudes and lower temperatures, pest and disease pressure is less severe on average. Low-potential areas are Thika, Murang'a, Maragua and the southern half of Kirinyaga District dominated by the undulating Mwea plains. Kiambu is outside of this classification. Although agro-ecological production conditions are favorable there, Kiambu District was chosen because of its closeness to Nairobi and the peri-urban nature of farming.

Within each district, banana-growing villages, specifically those where TC activities took place in the past, were purposively selected. Within the villages, farm households were sampled randomly. However, due to relatively low TC adoption rates, separate village lists of adopters and nonadopters were prepared, and adopters were oversampled to have a sufficient number of observations for robust estimates. In total, 385 banana farmers, 223 TC adopters, and 162 nonadopters, were sampled. In each sample household, the household head was interviewed using a structured questionnaire specifically designed for this purpose. The questionnaire was pretested prior to formal data collection to ensure content validity and clarity. Interviews were carried out in the local language by trained enumerators, who were supervised by the researchers.

While the sample is not nationally representative, the two subsamples are considered representative of banana farmers in Central and Eastern Provinces of Kenya. The fact that only villages with TC dissemination activities were selected could be considered a drawback, because this may potentially limit observed institutional and infrastructure variability. However, Fischer and Qaim (2012), who used a different sample to analyze the impacts of collective action among banana-growing households in the central highlands of Kenya, showed that there is no systematic difference in terms of household and village characteristics between regions with and without TC dissemination activities.

However, as consistent estimation of the adoption parameters in the ATE framework hinges on the assumption of randomly sampled data, the fact that we used a stratified sampling design and oversampled TC adopters needs to be accounted for (Wang et al., 2009). To correct for this, we developed sampling weights based on the estimated number of adopters relative to the total number of banana farmers in Central and Eastern Provinces (Njuguna et al., 2010). The sampling weights used represent the inverse of the probability that an observation is included in the sample (Wooldridge, 2007). These weights are used at all stages of the econometric analysis and predictions in Section 5.

4.2. *Definition of dependent variables*

Technology adoption is defined here as the use of at least a few TC banana plantlets by a farm household. The majority of adopters in our sample still had banana plots planted with traditional suckers or had intercropped TC with traditional bananas; only 8% had fully adopted TC at the time of the survey. The adoption decision is relevant only to a nonrandom subsample of the respondents who are aware of the technology's existence. This is what we call awareness exposure, which we assessed by asking farmers whether or not they have heard of TC bananas. Awareness exposure is measured as a dummy, which takes a value of one if the farmer responded "yes" to this question, and zero otherwise. Only those farmers who had heard about TC were then asked whether they also knew the attributes and performance of TC bananas. The binary answer to this question was used to construct the knowledge exposure dummy.[2] Obviously, farmers' responses to this second question are based on own perceptions rather than an objective knowledge assessment. Some follow-up questions on perceptions about TC technology were asked to farmers who responded "yes" to both questions, as is detailed further below.

It should be stressed that awareness and knowledge exposure are conceptually and empirically different. While adoption without awareness is not possible, one can actually start using a technology without really knowing its performance attributes. Also, since awareness precedes knowledge, awareness exposure is featured in knowledge exposure. Of the 385 farmers in the sample, 92% were aware of TC bananas, while 74% reported knowing the technology. Accounting for the deliberate oversampling of TC adopters, the weighted share of awareness and knowledge exposed farmers is 86% and 47%, respectively. These shares are higher than in other parts of Kenya. They probably also somewhat overestimate TC exposure in Central and Eastern Provinces, because we only sampled farm households from villages with TC dissemination activities.

4.3. *Explanatory variables and descriptive statistics*

The literature about agricultural innovation adoption has shown that the adoption decision depends on a variety of farm, household, and contextual characteristics (Doss, 2006; Feder et al., 1985). We broadly differentiate between human capital, assets and financial capital, social capital, and location characteristics, as shown in Table 1. The disaggregation by adoption status reveals that TC adopters are significantly older and better educated than nonadopters.

In terms of gender, we do not observe significant differences. Adopting and nonadopting households are both predominantly male headed. A gender perspective is particularly interesting here, because banana has traditionally been a woman's crop in Kenya, primarily grown for subsistence purposes. On the other hand, as is known from other contexts, the process of agricultural commercialization can be associated with changing gender roles, especially when new technologies are involved (von Braun et al., 1989).

TC adopters are more wealthy than nonadopters in terms of farm size (land owned) and also nonland productive assets. Looking at the income variables, no significant differences are observed. We deliberately excluded income derived from banana production to reduce possible endogeneity problems in estimation. We do observe, however, that a larger share of nonadopters is affected by credit constraints. In the survey, we captured formal and informal credit sources, both of which can play an important role for innovation adoption (Smale et al., 1994). Adopters also use more hired labor than nonadopters (again the banana enterprise is excluded), as can be seen from higher total wage payments in Table 1. This may be another indication of their higher liquidity.

To capture access to information, we asked farmers to mention all their formal and informal sources of agricultural information. Following this, we asked them how easily they can obtain reliable information about agricultural practices and innovations when needed, with "very easy," "easy," "difficult," and "very difficult" as possible answers. From these answers, we constructed an information constraint dummy, which takes a value of one for the latter two options and zero otherwise. This variable differs from the TC knowledge exposure dummy, because it did not refer to any specific crop or technology, but to agricultural production in general. Table 1 shows that nonadopters of TC feel much more information constrained than adopters. Adopters have significantly more contacts with professional extension workers. Moreover, informal sources of information, such as neighbors or other members in social networks, can also play an important role in innovation adoption, as was recently shown by Bandiera and Rasul (2006) and Matuschke and Qaim (2009). Indeed, Table 1 reveals that TC adopters are more often members of community-based groups, such as farmer or church associations. Likewise, adopters are significantly more likely to know the location of a TC nursery than nonadopters.

Similar to Matuschke and Qaim (2009), we also asked farmers to name their three most important social network contacts; for respondents aware of TC technology we further asked who of these network contacts had adopted this technology ahead of them. In this respect no significant differences between adopters and nonadopters can be observed. Nor do we observe any significant differences in terms of the location

[2] Farmers with a zero dummy value for awareness exposure were automatically assigned a zero value also for knowledge exposure.

Table 1
Descriptive statistics of sampled farm households

	Full sample ($N = 385$)		Adopters ($N = 223$)		Nonadopters ($N = 162$)	
	Mean	SD	Mean	SD	Mean	SD
Human capital						
Age of household head (years)	58.2	13.6	59.8***	13.2	56.0	13.8
Education of household head (years)	8.5	4.0	9.1***	4.1	7.7	3.8
Banana experience (years)	25.7	14.7	26.4	15.0	24.7	14.2
Time spent on farm (days per month)	23.3	4.6	23.4	4.5	23.1	4.7
Female headed (% of households)	17.7	–	17.0	–	18.5	–
Household size (members)	4.6	2.0	4.6	2.0	4.6	2.0
Proportion of crops sold to market[a] (%)	44.4	29.0	44.8	29.2	43.7	28.9
Assets and financial capital						
Farm size (acres)	3.30	3.01	3.83***	3.36	2.57	2.27
Value of nonland productive assets	178.8	224.2	216.0***	248.9	127.2	172.3
Value of investment in irrigation (‘000 K.shs)	5.6	12.8	7.4***	15.0	3.1	8.2
Agricultural wage payments[a] (‘000 K.shs per year)	14.8	22.9	18.4***	25.3	9.9	17.8
Per capita off-farm income (‘000 K.shs per year)	23.3	36.3	23.4	36.6	23.4	36.1
Per capita farm income[a] (‘000 K.shs per year)	25.0	43.1	24.5	28.6	25.8	57.5
Per capita total income[a] (‘000 K.shs per year)	48.5	59.8	47.9	48.9	49.4	72.5
Credit constrained (% of households)	40.1	–	33.6***	–	49.1	–
Social capital and access to information						
Information constrained (% of households)	29.4	–	19.7***	–	42.6	–
Extension contacts (times per year)	4.8	19.6	6.9**	25.4	1.8	3.2
Group membership (% of households)	90.9	–	96.9***	–	82.7	–
Farmer knows a TC nursery (%)	75.6	–	95.1***	–	48.8	–
TC adoption by social network (% of netw. contacts)	17.2	28.8	15.2	27.9	20.0	29.8
Location characteristics						
Distance to closest all-weather road (km)	3.4	3.8	3.6	4.0	3.3	3.5
Distance to closest input shop (km)	3.6	4.2	3.4	3.5	3.8	5.1
Distance to closest banana market (km)	5.0	15.5	5.5	20.1	4.4	3.7
Distance to main water source (m)	169	658	142	550	207	784
Located in high-potential area (% of households)	53.0	–	52.5	–	53.7	–
Located in Kiambu (% of households)	13.3	–	13.9	–	12.3	–

Notes: ***, **, and * imply that mean values for TC adopters are significantly different from those of nonadopters at the 1%, 5%, and 10% level, respectively. The exchange rate in December 2009 was: US \$1 = K.shs 76.
[a]These variables exclude the banana enterprise.

characteristics, shown in the lower part of Table 1. This should not surprise because we sampled both adopters and nonadopters in the same villages.

5. Results and discussion

5.1. *Farmer perceptions of TC banana*

During the survey, we had also asked farmers about their perception of TC banana and its attributes. As explained above, these questions were only asked to those who reported to be knowledge exposed. We listed a number of agronomic and quality attributes, as shown in Table 2, for which farmers had to indicate whether TC technology has a positive, negative, or no influence, as compared to bananas propagated through traditional suckers. We clarified to respondents that this was not a test, but that we were interested in the farmers' subjective attitudes. Overall, TC bananas are perceived as earlier maturing, higher yielding, and more uniform in terms of growth and production (Table 2).

However, TC bananas are generally perceived as more susceptible to water stress and drought. Many farmers also perceive them as more susceptible to pests and diseases, while others saw no difference in this respect between TC and traditional bananas. Almost all farmers dislike the high cost of TC plantlets. The average price of a TC plantlet is K.sh 83; it ranges between K.sh 40–130, depending on the source, transport costs, and whether or not the price is subsidized. The majority of farmers is also aware of the higher input requirements associated with TC and considers this as a disadvantage.

Considering all pros and cons, 85% of the adopters and 59% of the nonadopters classified TC bananas as superior to traditional suckers. Perception differences between adopters and nonadopters can partly be explained by different sources of information. Figure 1 shows that most adopters acquired TC-related knowledge from formal sources, such as NGOs or extension agents, whereas most nonadopters obtained their

Table 2
Farmer perceptions about attributes of TC in comparison to traditional bananas

Attribute	Farmer classification	The influence of TC technology is (in %)		
		Positive	Negative	No influence
Early maturity***	Adopters	95.5	0.9	3.6
	Nonadopters	80.0	5.0	13.3
Yield and bunch size**	Adopters	85.2	5.4	9.4
	Nonadopters	71.7	15.0	11.7
Pest and disease resistance*	Adopters	17.5	43.9	38.6
	Nonadopters	8.3	53.3	36.7
Drought and water stress resistance**	Adopters	4.5	90.1	5.4
	Nonadopters	0.0	86.7	11.7
Market price received per bunch**	Adopters	29.7	2.7	67.6
	Nonadopters	23.3	5.0	70.0
Production input requirements	Adopters	3.1	70.0	26.5
	Nonadopters	5.0	56.7	36.7
Pulp color*	Adopters	43.2	2.3	54.5
	Nonadopters	31.7	5.0	61.7
Fruit taste***	Adopters	54.3	3.1	42.6
	Nonadopters	35.0	5.0	56.7
Cost of planting material	Adopters	3.1	95.1	1.8
	Nonadopters	1.7	94.9	1.7
Uniformity of production***	Adopters	82.1	4.0	13.9
	Nonadopters	45.0	5.0	48.3

Notes: ***, **, and * imply that the perceptions of adopters and nonadopters are statistically different at the 1%, 5%, and 10% level, respectively (based on chi-square tests).

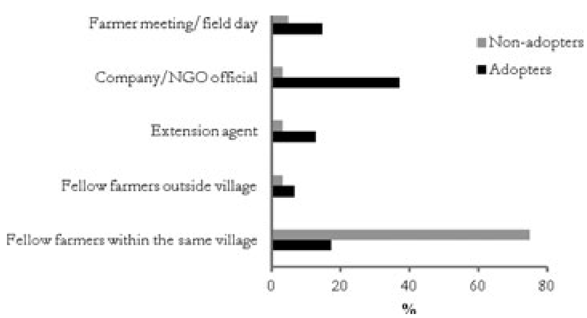

Figure 1. Sources of TC knowledge among adopters and nonadopters.

information from fellow farmers. Both information sources may come with a certain bias. NGOs and extension agents often demonstrate the benefits of innovations using well-managed demonstration plots with conditions that not all farmers can reproduce. On the other hand, through informal channels negative information could spread faster and more widely than positive information. In any case, information dissemination seems to be an important aspect that is likely to influence TC banana adoption.

5.2. Regression results

As explained in Section 3, the regression analysis follows two stages. In the first stage, probit models are used to analyze the determinants of TC awareness and knowledge exposure. In the second stage, probit models that control for heterogeneous awareness and knowledge exposure are used to estimate unbiased adoption parameters.

Before presenting the results, discussion of potential issues of endogeneity is important. One of the interesting features of the CI assumption in the ATE framework is that it does not require the covariates that determine information exposure and adoption to be exogenous (Diagne and Demont, 2007). The only requirement is that the covariates are determined outside the model (Heckman and Vytlacil, 2005), implying in our case that their values are unaffected by the exposure "treatment." For most of our explanatory variables, this can be safely assumed (Table 1). For instance, characteristics such as age, education, gender, or location are not influenced by TC awareness or knowledge exposure. Likewise, farm size and other productive assets are unlikely to change simply by being aware or knowing more about TC technology.

Variables related to commercial orientation of the farm and household income may potentially be affected by new information, but as information exposure in our context focuses only on one very specific banana technology, we do not expect significant spillovers to other economic activities. As mentioned above, we exclude the banana enterprise in the definition of some variables where endogeneity may potentially be expected. The information constraint is also not directly related to TC awareness or knowledge exposure; it captures access to agricultural information more generally, not specific for the banana enterprise.

For group membership, we avoided endogeneity problems by asking farmers who are affiliated to groups when exactly they became members. In almost all cases, membership had started before TC was introduced to the region. For the "TC adoption by social network" variable, we only counted network contacts as adopters when they had adopted prior to the farmer, to reduce the reflection problem in social interactions (Manski, 2000). This does not automatically preclude the possibility of reverse causality in information flows, but it may not be unrealistic to assume that farmers who adopted TC earlier were also earlier in terms of awareness and knowledge exposure. The only variable that may well be influenced by the exposure treatment is "farmer knows a TC nursery," which we only include in the second-stage adoption models. To test for potential problems, we also ran these models without this variable, which did not change the other coefficient estimates significantly. Hence, we kept this variable, as knowledge of a TC nursery can be seen as an indicator of the efficiency of seed systems, which is known to be an important determinant of technology adoption (e.g., Doss, 2006; Shiferaw et al., 2008).

5.2.1. Determinants of TC awareness and knowledge exposure

Table 3 presents results of the first-stage models that explain TC awareness and knowledge exposure, expressed in terms of

Table 3
Determinants of TC awareness and knowledge exposure

	TC awareness exposure		TC knowledge exposure	
	Marginal effects	z-Value	Marginal effects	z-Value
Age of household head (years)	−0.008	−0.59	−0.055**	−2.27
Age squared	9.017E-05	0.75	5.123E-04**	2.38
Education of household head (years)	0.013**	2.21	−0.021*	−1.82
Banana experience (years)	0.001	0.21	0.040***	4.18
Banana experience squared	−9.316E-05	−1.06	−7.366E-04***	−4.43
Time spent on farm (days per month)	0.004	1.09	−0.018**	−2.12
Female-headed household (dummy)	−0.008	−0.17	−0.213**	−2.42
Farm size (acres)	0.022	1.47	0.025*	1.82
Value of nonland productive assets (‘000 K.shs)	1.347E-04	1.08	4.801E-04**	2.42
Share of off-farm income [a] (%)	−2.84E-05	−0.09	1.74E-04	0.47
Credit constrained (dummy)	−0.023	−0.53	0.012	0.15
Information constrained (dummy)	0.003	0.07	0.003	0.03
Group membership (dummy)	0.066	1.10	0.309***	2.60
TC adoption by social network (%)	0.001	1.32	0.001	1.16
Distance to closest all-weather road (km)	0.011**	2.07	0.002	0.20
Distance to closest input shop (km)	−0.004	−1.25	−0.022**	−2.18
Distance to closest banana market (km)	−0.001	−0.65	0.001	0.38
Located in high-potential area (dummy)	−0.048	−1.13	0.068	0.89
Located in Kiambu (dummy)	0.097	1.28	0.112	0.93
Number of observations	382		383	
Pseudo R^2	0.220		0.159	
LR chi^2 (prob>chi^2)	41.61***		62.13***	
Log likelihood	−122.77		−224.56	

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Estimates are marginal effects evaluated at weighted sample means.
[a]These variables exclude the banana enterprise.

marginal effects at weighted sample mean values. As can be seen, better educated farmers are more likely to be aware of the existence of TC bananas. Each additional year of formal education increases the probability of awareness by 1.3 percentage points. TC awareness is also higher in areas with poor access to roads. A possible explanation is that in more remote locations there are fewer economic alternatives to farming and thus a greater incentive for farmers to actively search for relevant agricultural innovations.[3] Other variables are not significant in this model, which is not completely unexpected: as TC technology has been promoted in the survey regions for many years, awareness is widespread, regardless of the individual socioeconomic conditions.

The second model in Table 3, which explains TC knowledge exposure, has more significant variables. Older farmers are less likely to have profound knowledge about TC bananas. This is plausible, because older farmers are often less innovative than their younger colleagues. The positive and significant estimate for the square term of age indicates that this effect is diminishing. Strikingly, education has a negative effect on TC knowledge exposure, possibly implying a shift of skilled manpower to other economic activities, including off the farm. This is particularly interesting given that the education effect in the awareness model was positive. Obviously, hearing about a technology and acquiring more profound knowledge are not necessarily processes that are influenced by the same socioeconomic factors. Hence, it is important to differentiate.

Experience with banana farming has a positive effect on TC knowledge exposure, which may be related to the skills and farsightedness needed for acquiring useful information. Each additional year of experience with banana growing increases the probability of knowledge exposure by 4 percentage points, although the effect is diminishing, as the negative square term demonstrates. The time spent on the farm has a negative impact on knowledge exposure, probably because more on-farm time means less outside interactions. Likewise, female-headed households are less likely to know TC, which can be due to a gender bias in extension efforts and informal information flows. The positive and significant coefficient for group membership points at the important role of social networks for knowledge dissemination.

Farmers with larger landholdings and more productive assets are more likely to be exposed to TC knowledge. For them it is easier to afford the cost of knowledge acquisition. Furthermore, it is likely that information flows are biased towards community members of higher social status, which tends to be correlated with asset ownership. In terms of location, distance to the closest farm input shop influences knowledge exposure in a negative way. This is plausible; research in other contexts has also shown that input suppliers are important sources of

[3] Even though we sampled households only in villages with TC dissemination activities, awareness was more widespread on average in locations further away from all-weather roads.

information for smallholder farmers, especially in situations where the formal extension service is not very effective (e.g., Matuschke and Qaim, 2009). These results indicate that information dissemination does not occur randomly, but that there are factors that influence knowledge exposure in a systematic way.

5.2.2. Determinants of TC adoption

Table 4 presents results of the TC banana adoption analyses with three alternative model specifications. Model (1) presents results of the classical adoption probit without accounting for exposure bias, whereas models (2a) and (2b) present ATE-corrected results, controlling for possible exposure bias introduced by (a) heterogeneous awareness of the existence of TC, and (b) heterogeneous knowledge about the attributes and performance of TC. All values reported are marginal effects evaluated at weighted sample means.

There are many similarities observed across the three models, at least in terms of signs and significance levels. Education, group membership, and knowing where a TC nursery is located are factors that influence the likelihood of TC adoption positively. Knowing where a nursery is located is important, in order to be able to source TC planting material. Perceived lack of access to seeds or planting material was shown to be a constraint for the adoption of new crop technologies also in other contexts (e.g., Diagne, 2006; Doss, 2006). On the other hand, information constraints and off-farm income share have a negative effect on adoption. While off-farm income may provide the financial liquidity needed for TC adoption, it is also an indication of a specialization away from agriculture, which can entail less interest in new technologies.

Interesting to observe is that the share of social network members who adopted TC earlier has a negative impact in all three models. In other words, the more TC adopters there are in the personal network, the less likely it is that the farmer herself also adopts. This result could indicate that TC adoption is not beneficial for all, so that the experience of current users does not encourage other farmers to adopt.[4] As discussed above, successful TC adoption does not just involve switching to new planting material but also requires higher input regimes and proper plantation management, which is not always followed. Own field observations revealed that even the farmer-managed demonstration plots are not always well maintained, which is partly due to constraints in continued funding and technical support. This can influence information flows and technology perceptions. It can possibly also explain the negative influence of banana experience on TC adoption: more experienced farmers may be able to observe and assess more realistically how a new technology performs under different conditions.

Yet another explanation for the negative social network effect could be that some nonadopters use second-generation TC suckers obtained from their peers, thus reducing the perceived need to adopt the original planting material themselves.[5] Even though this practice is discouraged by agronomists, TC suckers seem to be preferred by some over traditional suckers. Indeed, a few TC adopters in our survey reported having given second-generation suckers to their friends and neighbors.

Strikingly, farmers in high-potential banana areas are also less likely to adopt TC technology. While this may be surprising on first sight, it is not implausible. In high-potential areas, pest and disease pressure is lower, and bananas grow relatively well even under poor management conditions, so that the need for TC may not be felt to the same extent as in low-potential areas. Moreover, finding good suckers that can be used as planting material is less of a problem in more favorable areas. This suggests that many farmers see TC as a form of readily available and clean planting material rather than a technology with superior traits. Furthermore, it underlines the fact that the smallholder farmers still consider banana primarily as a security crop that produces some yields even without much effort. In their study in Uganda, Edmeades and Smale (2006) also found that farmers in regions with favorable banana growing conditions were less interested in new technologies.

Farm size and ownership of other productive assets do not influence adoption significantly, indicating that the technology as such is scale-neutral. Farmers can buy just a few TC plantlets for a tiny garden plot or also several hundred for a larger plantation. This was also found in many other studies related to the adoption of new crop technologies, when institutional factors, which are often correlated to asset ownership, are properly controlled for (Edmeades and Smale, 2006; Feder et al., 1985; Matuschke et al., 2007; Schipmann and Qaim, 2010). However, it should be stressed that farm size and nonland assets have a significant influence on the likelihood of knowledge exposure, as was shown above.

So far we have only discussed the results in Table 4 that are consistent across the different models, but we also observe a couple of notable differences. When only accounting for heterogeneous awareness exposure (model 2a), the estimated marginal effects are more or less similar to those in the classical adoption model. This is in contrast to the findings of Diagne and Demont (2007), who found bigger differences in their estimates. But the reason for these differences is simple: while in Diagne and Demont (2007) only 9% of the survey respondents were aware of the new technology, in our case awareness is much more widespread. Hence, awareness exposure bias is small. However, when accounting for heterogeneous knowledge exposure (model 2b), the marginal

[4] One could also imagine that farmers get more reluctant to adopt when many others in one location have already adopted a new, productivity-increasing technology, because they anticipate product oversupply and hence marketing problems. However, given increasing demand for bananas from urban centers and banana trade channels that have improved in the region in recent years (Fischer and Qaim, 2012), this is probably not a dominant perspective among farmers.

[5] In our study, we only consider farmers as adopters when they use first-generation TC plantlets from the laboratory.

Table 4
Determinants of TC banana adoption

	(1) Classical adoption model		(2) ATE-corrected adoption models for exposure to			
			(a) TC awareness		(b) TC knowledge	
	Marginal effects	z-Value	Marginal effects	z-Value	Marginal effects	z-Value
Age of household head (years)	−0.003	−0.64	−0.004	−0.68	0.018	1.20
Age squared	5.262E-05	1.22	6.306E-05	1.21	−7.685E-05	−0.58
Education of household head (years)	0.007**	2.25	0.007**	2.02	0.024***	2.59
Banana experience (years)	−0.008***	−3.02	−0.009***	−2.78	−0.053***	−4.85
Banana experience squared	1.369E-04***	3.07	1.489E-04***	2.77	9.088E-04***	4.59
Time spent on farm (days per month)	0.002	0.92	0.002	0.74	0.008	1.37
Female-headed household (dummy)	0.023	0.98	0.023	0.84	0.164*	1.90
Household size	0.005	1.12	0.005	0.94	0.010	0.69
Farm size (acres)	0.003	0.63	0.003	0.50	−0.001	−0.09
Value of nonland productive assets (‘000 K.shs)	5.606E-05	0.93	6.435E-05	0.94	9.414E-05	0.54
Agricultural wage payments[a] (‘000 K.shs)	−1.126E-04	−0.26	−1.309E-04	−0.26	−2.835E-04	−0.24
Proportion of crops sold to market [a] (%)	−3.92E-04	−1.03	−4.39E-04	−1.01	3.08E-04	0.29
Share of offfarm income [a] (%)	−4.31E-04*	−1.70	−5.07E-04*	−1.73	−1.26E-03*	−1.73
Credit constrained (dummy)	−0.032	−1.63	−0.035	−1.52	−0.109*	−1.88
Information constrained (dummy)	−0.049**	−2.47	−0.054**	−2.26	−0.181***	−2.76
Group membership (dummy)	0.172***	4.51	0.179***	4.13	0.462***	3.80
Farmer knows a TC nursery (dummy)	0.212***	7.91	0.229***	7.48	0.414***	3.47
TC adoption by social network (%)	−0.001*	−1.95	−0.001*	−1.76	−0.002**	−2.08
Distance to closest all-weather road (km)	0.004	1.60	0.004	1.38	0.004	0.52
Distance to closest input shop (km)	4.176E-04	0.18	4.526E-04	0.14	8.762E-03	0.81
Distance to closest banana market (km)	0.005*	1.80	0.005	1.53	0.012	1.15
Distance to closest water source (m)	2.846E-06	0.23	6.680E-06	0.36	4.234E-05	0.76
Located in high-potential area (dummy)	−0.039**	−1.98	−0.043*	−1.85	−0.167***	−2.63
Located in Kiambu (dummy)	0.010	0.33	0.007	0.19	−0.069	−0.67
Pseudo R^2	0.332		0.300		0.355	
LR chi^2 (prob>chi^2)	109.06***		97.84***		102.72***	
Log likelihood	−107.24		−114.09		−113.93	

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Estimates are marginal effects evaluated at weighted sample means.
[a]These variables exclude the banana enterprise.

effects differ more substantially from those in the classical adoption model. This underlines that differentiating between awareness and knowledge is important, especially when analyzing the adoption of knowledge-intensive technology packages such as TC bananas. Obviously, significant knowledge differences persist even more than 10 years after the first introduction of TC technology.

Taking a closer look at the differences in Table 4, we observe that the marginal effects in the knowledge exposure bias corrected model often tend to be bigger in their absolute values than those in the classical adoption model. For instance, the impact of education on the probability of adoption is more than three times bigger. The reason is the negative effect of education in the first-stage knowledge exposure model (see Table 3). Better educated farmers are less likely to acquire profound knowledge about TC banana (probably due to lucrative alternatives to banana farming), but once they know about TC, they are more likely to adopt than their colleagues with less education. These effects are blurred in model (1) of Table 4, while they are disentangled in model (2b). Similarly, the effects of banana experience and off-farm income are much stronger in model (2b), this time with negative signs.

There are also two variables that have insignificant effects in the classical model, but significant ones when controlling for knowledge exposure bias, namely credit constraint and female household head. While credits are rarely taken for meeting the cost of knowledge acquisition, this is different when it comes to actual adoption, which involves the purchase of relatively expensive TC plantlets. All other things equal, the probability of adopting TC is 11 percentage points lower among credit constrained farmers than among their colleagues who have better access to financial capital. For female-headed households, the probability of adoption increases by 16 percentage points, when heterogeneous knowledge flows are controlled for. This is a very remarkable result, especially in combination with the negative effect for the same variable in the TC knowledge exposure model (Table 3). Many previous studies have reported the dominance of men in adopting new farm technologies, but our findings suggest that this must not be the case when women have an equal chance to acquire sufficient knowledge about particular innovations. An important policy implication is that eliminating gender biases in extension systems and informal information flows should have high priority.

Table 5
Predicted adoption rates of TC bananas

	Awareness exposure			Knowledge exposure		
	Estimate	S.E.	z	Estimate	S.E.	z
ATE-corrected population estimates						
Predicted adoption rate in the full population (ATE)	0.154***	0.014	11.00	0.282***	0.037	7.63
Predicted adoption rate in exposed subpopulation (ATE_1)	0.174***	0.016	11.06	0.320***	0.025	12.92
Predicted adoption rate in unexposed subpopulation (ATE_0)	0.037**	0.011	3.44	0.248***	0.059	4.24
Joint exposure and adoption rate (JEA)	0.148***	0.013	11.06	0.150***	0.012	12.92
Population adoption gap (GAP)	−0.005**	0.002	−3.44	−0.132***	0.031	−4.24
Population selection bias (PSB)	0.019***	0.002	8.58	0.038	0.029	1.31
Observed sample estimates						
Exposure rate (N_e/N)	0.856***	0.025	33.74	0.468***	0.034	13.89
Adoption rate (N_a/N)	0.147***	0.013	11.30	0.148***	0.013	11.31
Adoption rate among the exposed subsample (N_a/N_e)	0.172***	0.015	11.30	0.317***	0.028	11.31

Notes: *** and ** denote statistical significance at the 1% and 5% level, respectively. Robust standard errors are reported. All results take the oversampling of adopters into account through weighting.

5.3 Predicting TC adoption rates

Building on the estimation results, Table 5 presents predicted adoption rates with and without ATE correction for awareness and knowledge exposure bias. The weighted TC banana adoption rate estimate for the total sample, which is shown in the lower part of Table 5, is around 15%. This matches with other estimates for the Central and Eastern Provinces, where TC adoption is higher than in the rest of Kenya (Njuguna et al., 2010).

The joint adoption and exposure rate (JEA) estimates are also in a magnitude of 15% for both ATE corrected models. Similarity between the observed adoption rate estimates and JEA should be expected (Diagne and Demont, 2007). However, neither the observed adoption rates nor JEA are good indicators of the potential population adoption rate because of partial exposure. Correcting for heterogeneous awareness exposure, the predicted adoption rate for the full population (ATE) is 15.4%. This is still almost the same, because of widespread TC awareness. The difference is bigger when correcting for knowledge exposure. Given universal knowledge about TC attributes and performance, but otherwise unchanged conditions, the adoption rate could almost double to 28%. As explained in Section 3, subtracting ATE from JEA results in the population adoption gap (GAP) due to lack of TC knowledge, which is equivalent to 13%.[6] This implies that there is still substantial potential to increase TC adoption in the region, if all farmers have a chance to better understand the technology.

The predicted adoption rate in the subpopulation that is already knowledge exposed is calculated as the ATE on the treated (ATE_1), which is 32%. This rate is slightly higher than that of the full population (ATE), indicating positive population selection bias (PSB). This is expected due to the fact that the most innovative farmers self-select into treatment (knowledge exposure). The predicted adoption rate in the unexposed subpopulation is calculated as the ATE on the untreated (ATE_0), which is 25%.

PSB for awareness exposure is quite small but significant, implying that potential TC adopters are more likely to be awareness exposed first. PSB for knowledge exposure is bigger in magnitude but insignificant. Some farmers actually start using TC before knowing more about its attributes, which may potentially result in undesirable performance and dissatisfaction. Awareness and knowledge dissemination should go hand in hand, which is particularly important for knowledge-intensive technologies.

6. Conclusions

We have analyzed the role of information dissemination in technology adoption using the case of TC bananas in Kenya. Due to various reasons, organizations that promote and deliver new technologies to farmers, such as extension services or NGOs, will rarely be able to cover all potential adopters with their efforts, leading to heterogeneous information exposure. Under such conditions, classical approaches of adoption analysis may be inconsistent due to selection bias. We have accounted for such bias by using the ATE framework and estimating adoption parameters at individual and population levels. Building on a primary dataset of Kenyan banana farmers, we have considered two different levels of information exposure, namely awareness exposure (being aware of the existence of the new technology) and knowledge exposure (knowing more about the attributes and performance of the technology).

When only controlling for heterogeneous awareness exposure, the estimated marginal effects in our example are very similar to those of the classical adoption model. This is due to the fact that TC bananas have already been promoted for more than 10 years in Kenya, so that awareness among

[6] The population adoption gap due to heterogeneous knowledge exposure may be somewhat underestimated with our data, because only farm households in villages with TC dissemination activities were sampled.

farmers is widespread. However, when accounting for heterogeneous knowledge exposure, the differences vis-à-vis the classical adoption model become more pronounced, as knowledge about the attributes and performance of TC bananas is much less widespread. Many of the marginal effects increase in absolute terms, meaning that these would be underestimated with the classical model. Cases in point are the effects of education, access to information, and the role of groups and social networks.

There are also variables that are insignificant in the classical model but turn out significant and important in the model that corrects for heterogeneous knowledge exposure. For instance, female-headed households are more likely to adopt TC, which is particularly important from a policy perspective, as in Kenya bananas are predominantly managed by women. Even though many adoption studies report that new agricultural technologies are more adopted by men, our findings suggest that this can even be the other way around when women have an equal chance to acquire appropriate knowledge about the innovation.

These results underline the importance of accounting for information exposure in adoption research. Because factors that influence information exposure may vary from those that influence actual adoption, mixing them, as is implicitly done in classical adoption models, can lead to erroneous policy recommendations. The results also emphasize that differentiating between awareness and knowledge is important in adoption studies.

At the population level, we found that adoption rates of TC bananas could be significantly higher with better knowledge exposure. Hence, the question as to how smallholders can access good information about innovations on a wider scale must be addressed from a development policy perspective. This is particularly important for knowledge-intensive technologies that require intensive training and extension efforts. TC bananas are one example, but the same holds true for many agronomic innovations such as precision farming, conservation agriculture, or other natural resource management practices (Lee, 2005; Wollni et al., 2010). Implementing sustainable technical change in smallholder agriculture remains a policy challenge for many developing countries; this is not only an issue of developing new technologies but also one of delivering technologies and related knowledge to farmers. As traditional extension services are either very expensive or ineffective or both, new and more efficient models of innovation delivery have to be sought and implemented on a wider scale. Such new delivery models should build on existing social structures and networks at community levels. Moreover, to reduce outreach costs, greater use of modern information and communication tools could potentially be made.

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