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Submitted Article

Big Constraints or Small Returns? Explaining Nonadoption of Hybrid Maize in Tanzania

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Abstract *New technologies are often not widely adopted by farmers in Africa. Several adoption constraints have been discussed in the literature, including limited access to information. Using data from maize farmers in Tanzania, we challenge the hypothesis that limited information is an important constraint for hybrid seed adoption. While we find an adoption gap from lack of hybrid awareness, this gap is sizeable only in regions where productivity gains of hybrids are small. Hence, awareness of a new technology may be a function of expected returns. Other constraints related to assets and credit are not significant. We conclude that not adopting a technology is not always a sign of constraints but may also indicate low benefits from its use.*

Key words: Technology adoption, technology exposure, adoption gap, small farms, Africa.

JEL codes: O33, Q12, Q16.

Agricultural technology is a fundamental driving force for rural development. But the adoption rate of modern technologies, such as improved seeds and fertilizers, is low in many developing countries (Foster and Rosenzweig 2010). For instance, in developing countries only around 50% of the cultivated maize area is under modern varieties (MVs), including hybrids and improved open-pollinated varieties (OPVs), whereas in developed countries the MV share is close to 100%. There are also large differences in yield. Mean maize yields are 4 t/ha and 9 t/ha in developing and developed countries, respectively (Shiferaw et al. 2011).

In Sub-Saharan Africa, the adoption of MVs is still lower than in other developing regions, which cannot be explained by issues of technology unavailability alone (Byerlee and Heisey 1996; Lunduka et al. 2012). The search for reasons has concentrated on several adoption constraints. One such constraint is limited access to information; being aware of a technology is a necessary condition for its adoption (Diagne and Demont 2007). Other possible constraints are market imperfections for insurance and credit (Foster and Rosenzweig 2010). Policy recommendations usually focus on alleviating such constraints through the provision of extension, insurance, or credit schemes. A recent study has suggested that behavioral biases may also play an important role (Duflo et al. 2011). Behavioral biases are related to market imperfections but still conceptually different. For instance, farmers may have access to information, credit, and insurance, but they may still not adopt due to myopic discounting. A policy response could be in the form of "nudges" to correct behavioral biases. Yet another possibility is that nonadoption is neither the result of constraints nor behavioral biases. Unconstrained, rational nonadoption of a particular technology would imply that the returns to adoption are negative or insignificant (Suri 2011). Which of these reasons dominates is an important question for policymaking that seeks to facilitate innovation adoption and productivity growth.

In this article, we analyze the adoption of hybrid maize technology in Tanzania by exploring the possible reasons for nonadoption by some farmers. Maize is the main staple food in Tanzania and is primarily grown by smallholder farmers. We use survey data from two regions of Tanzania, the north where hybrid adoption rates are relatively high, and the east where adoption is much lower. The main research question we address is whether lack of awareness is an important factor in explaining the nonadoption of hybrid maize technology, especially in the east of Tanzania. In addition, we address two related questions: Is awareness of hybrid maize a function of the expected returns to this technology? Further, in cases where farmers were aware of the technology but did not adopt, what are the factors that may explain nonadoption? To the best of our knowledge, the link between information constraints and returns to adoption has never been analyzed in the empirical literature.

We use the average treatment effect (ATE) framework to estimate technology adoption rates and control for nonawareness bias, as proposed by Diagne and Demont (2007).[1] The results show that lack of awareness of hybrid seeds is not an important reason for nonadoption in Tanzania. The adoption gap caused by lack of awareness is not very large. Assuming full awareness, adoption rates would still differ considerably between the two regions, which we explain by insignificant yield effects of hybrid technology and thus low returns to adoption in the east. We also find that the spread of information about hybrids through extension and farmer networks is important in the north but not in the east, suggesting that awareness may be a function of expected returns. We do not find evidence for adoption constraints related to asset ownership or access to credit.

Background

There are multiple and sometimes conflicting reasons mentioned for the low adoption rates of MVs in Sub-Saharan Africa. One explanation is that

[1]*Diagne and Demont (2007) use the term "technology exposure", building on terminology used in the impact evaluation literature. Here, we prefer the term "technology awareness", which may be clearer for a broader readership. However, the underlying concept is identical.*

available MVs are not sufficiently adapted to local farmers' needs (Doss 2003). Indeed, Byerlee and Heisey (1996) argue that breeders have paid too little attention to local agroecological conditions, agronomic practices, processing characteristics, and seasonal labor availability. Suri (2011) uses a model that allows for heterogeneity in profitability and finds that many farmers in Kenya did not adopt hybrids because of limited benefits from doing so. However, Suri also shows that 20% of farmers are nonadopters who could derive high returns from hybrid adoption, suggesting that at least some farmers are constrained in their access to credit and inputs (Suri 2011).

Such infrastructure and institutional constraints, including poor market integration, communication, and transport, comprise a second cluster of explanatory factors (Chirwa 2005). Langyintuo et al. (2010) note that poorer farmers are less likely to adopt modern maize varieties due to cash and credit constraints. Smale et al. (1995) and Abebaw and Haile (2013) confirm that membership in credit clubs or farmer cooperatives increases the likelihood of adoption of MVs and fertilizers. In contrast, Duflo et al. (2008) argue that low technology adoption can be explained, at least in part, by farmers' behavioral factors. Based on randomized controlled trials, these authors identify low motivation to save as one important factor in nonadoption of technology. For instance, farmers may spend the income from one harvest entirely for immediate needs and desires, so that insufficient money is saved to buy seeds and other inputs in the next planting season. Duflo et al. (2011) suggest that simple interventions ("nudges") such as offering farmers the opportunity to buy fertilizer at the end of the previous season could help to increase adoption rates significantly.

These different explanations can be categorized as shown in table 1. Farmers can fall into one of four possible categories with respect to MV adoption, depending on the yield or profitability of the new varieties relative to traditional varieties and whether or not they are actually adopted. Each outcome is based on different theoretical lines of reasoning, leading to a specific set of policy interventions to further improve farmers' welfare.

In the first and best case, adoption of superior MVs is a rational and informed decision that is not constrained by limited access to seed dealers, credit, or other markets. In this case, no policy intervention is needed, except for promoting further improvement of MVs to ensure continuous rates of technological progress. The second possibility is that farmers do not adopt MVs, but would be better off if they did. Depending on the underlying reasons, suggested policy responses would be either investment into better functioning markets or nudges. The third option is farmers have adopted MVs that have lower yields or profitability than traditional varieties. This could be due to farmers still experimenting with the new varieties. In that case, the information delivered to farmers could be improved to support their learning process, and new, better-adapted varieties should be made available. It should be noted that farmers' varietal preferences may also be based on criteria other than yield or profitability. The fourth possibility is that MVs may be lower-yielding or less profitable than traditional varieties, but farmers are aware of this fact, which would explain low adoption rates (Suri 2011). An appropriate policy response would have to focus on promoting the development of MVs that are better adapted to farmers' conditions.

Several studies have examined information constraints to technology adoption. For example, Matuschke and Qaim (2009) argue that information constraints are one main obstacle to the adoption of hybrid seeds, and that

Table 1 Adoption Behavior, Impact, Causes, and Remedies

	MVs adopted	MVs not adopted
MVs have higher yield or profitability than traditional varieties	1. Based on experience or unbiased information provided by others, farmers correctly expect that the adoption of MVs is beneficial. *Remedy: Not needed. Continue promotion of MV development.*	2(a). Exogenous constraints are the major reasons for low adoption, including information and credit constraints. *Remedy: Invest in better functioning markets.* 2(b). Behavioral biases (e.g., lack of saving discipline) are the main cause. *Remedy: "Nudges".*
Traditional varieties have higher yield or profitability than MVs	3. Farmers are still experimenting or have preferences other than yield or profitability. *Remedy: Improve flow of unbiased information. Develop varieties better adapted to farmers' preferences.*	4. Lack of MVs adapted to farmers' conditions and preferences is responsible for low adoption rates. *Remedy: Develop varieties better adapted to farmers' conditions and preferences.*

Source: Authors' illustration.

active social networks can reduce such hurdles. Further, Kabunga et al. (2012a; 2012b) have analyzed the adoption of tissue culture (TC) bananas in Kenya, which is a relatively knowledge-intensive technology. While many farmers are aware of this technology, they often do not know how to use TC successfully, so adoption rates remain relatively low. Hence, information constraints play an important role in many contexts, but probably not in all.

Very few studies have estimated the returns to adoption of technologies that are alleged to be underutilized (Foster and Rosenzweig 2010). A recent exception is Suri (2011), who analyzed data on hybrid maize adoption in Kenya and found that a large proportion of nonadoption can be explained by low returns. On the other hand, there are few cases of widely-adopted technologies that do not deliver some form of benefits to farmers. This is plausible; at least for technologies in annual crops, farmers can observe the technology's performance and update their beliefs and choices for subsequent years accordingly. There is also evidence that the speed of adoption is higher when the benefits are large. Griliches (1957) showed that differences in diffusion and equilibrium adoption rates of hybrid maize between regions can be explained by differences in profitability. In India, the rapid and widespread adoption of genetically modified cotton can be explained by large yield and profit gains (Kathage and Qaim 2012).

Existing empirical studies have considered information constraints and the magnitude of technological benefits as two separate aspects in explaining adoption. This is surprising, because information flows can be a function of adoption returns. Positive impacts of a technology will be advertised by companies with the aim of reaching additional customers. Information about successful technologies will also spread through word-of-mouth. For example, Matuschke and Qaim (2008) observed that hybrid adopters who experienced sizeable positive returns are important sources of information for other farmers.[2]

Analytical Framework

Being aware of the existence of a new technology is a necessary condition for adoption. In rural areas of developing countries, where transaction costs are high and access to information is limited, it is quite common that not all farmers know about the existence of a new technology immediately. For instance, in their research in Cote d'Ivoire, Diagne and Demont (2007) found that a significant proportion of farmers was not aware of so-called NERICA rice varieties, even though these varieties had already been introduced several years earlier. The spread of information tends to be particularly slow when new technologies are propagated by extension services that cannot reach out to all regions of a country (Noltze et al. 2012; Kabunga et al. 2012a). When estimating technology adoption and adoption determinants in such situations, results may be misleading when lack of awareness is not controlled for.

We use the ATE framework to control for possible nonawareness bias in our analysis of hybrid seed adoption in Tanzania. The ATE framework is a tool from the impact evaluation literature dating back to the work of Rubin (1973). In impact evaluation, comparison is made between treated and untreated individuals, controlling for possible selection bias. Similarly, in the technology adoption context we differentiate between aware and unaware farmers, as proposed by Diagne and Demont (2007). Another recent application of the ATE framework to analyze technology adoption is the study by Kabunga et al. (2012a).

In the adoption context, "treatment" means awareness of the particular technology, and the ATE is the "true" adoption rate when all members of the population have become aware of it. Diagne and Demont (2007) demonstrate that the true adoption rate cannot be consistently estimated unless awareness is controlled for. The adoption rate observed in a sample from a population that is not completely aware is probably lower, since at least some of the unaware farmers might adopt if they were aware (Diagne and Demont 2007). Nor can the true population adoption rate be estimated consistently from the subsample of aware farmers due to selection bias in awareness. Also, the determinants of adoption cannot be estimated consistently unless they are separated from the determinants of awareness.

Identification of Treatment Effects

The ATE framework is used to separate awareness and adoption and to calculate adoption gaps resulting from a lack of awareness. The two main components of this framework are a binary treatment variable w that refers to awareness status, and a binary outcome variable y that refers to adoption status. For each farmer i, the treatment effect is defined as the difference of adoption status if aware, and adoption status if not aware ($y_{1i} - y_{0i}$). This

[2] *Conversely, one can expect that highly negative impacts of a technology will also be communicated extensively as a warning to others, while insignificant impacts may not be reported and noticed widely. This suggests a possible U-shaped relationship between technology awareness and adoption returns. Testing the functional form of this relationship may be an interesting topic for further research. Here we attempt to establish empirically that a relationship exists.*

effect corresponds to $E(y_1 - y_0)$ at the population level, where it is called *ATE*, or the predicted adoption rate in the full population under the assumption of full awareness. The value of y_{0i} is always equal to zero, since awareness is a necessary condition for adoption. Therefore, *ATE* reduces to $E(y_1)$. For aware farmers, y_{1i} is observed and called the average treatment effect on the treated (ATE_1). For unaware farmers, y_{1i} is not observed and called the average treatment effect on the untreated (ATE_0). The observed sample adoption rate is called the joint awareness and adoption rate (*JAA*) because observed adoption implies awareness.[3] The difference between *JAA* and *ATE* is called the adoption gap (*GAP*), which indicates the degree to which a lack of awareness reduces the adoption rate. The population selection bias (*PSB*) is defined as the difference between ATE_1 and *ATE*, and shows the extent of bias in an estimate of the adoption rate under full awareness based on the observed adoption rate among the aware subsample.

A key problem in the treatment effect literature is the proper identification of the treatment effect. If treatment is not randomly assigned, observed differences in the outcome variable between the treated and untreated subpopulations cannot simply be interpreted as the treatment effect. The reason is that individuals that self-select into treatment may have different values for the outcome variable even without treatment; that is, $E\ (y_0 \mid w = 1) \neq E\ (y_0 \mid w = 0)$. Systematic differences may be due to observed and unobserved factors. Especially when unobserved factors matter, valid instruments are usually required for proper identification (Wooldridge 2002).

However, in the adoption context identification is easier because the outcome variable is binary and the potential outcome is $y_0 = 0$ for both the treated and untreated subpopulations; that is, $E\ (y_0 \mid w = 1) = E\ (y_0 \mid w = 0)$. Under these conditions, the conditional independence (CI) assumption holds, which states that the treatment status w is independent of potential outcome status y_1 and y_0 conditional on a set of observed covariates x (Wooldridge 2002; Diagne and Demont 2007). The average treatment effect on the treated conditional on x, $E\ (y_1 \mid x, w = 1)$, is identical to the average treatment effect conditional on x, $E\ (y_1 \mid x)$. The CI assumption in this context does not imply that w and y cannot be influenced by unobservables, but that the existence of unobservables does not bias estimates of the treatment effects. Hence, instrumental variables are not required for identification.

Estimation Procedure

The *ATE* estimators based on the CI assumption can be estimated using either parametric or nonparametric regression methods. We employ parametric regression in a model for the conditional expectation of the observed variables y, x, and w

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

where g is a function of observed covariates $\boldsymbol{x}$ determining adoption and a parameter vector $\boldsymbol{\beta}$. We follow specifications of the parametric regression models as detailed in Diagne and Demont (2007). The parameter vector $\boldsymbol{\beta}$ can be estimated by maximum likelihood techniques using observations in

[3] *The* JAA *is equivalent to* JEA *(joint exposure and adoption rate) in Diagne and Demont (2007). As explained, we use the term "awareness" instead of "exposure". Other notations are as they appear in Diagne and Demont (2007).*

the aware subsample with y as dependent and $\boldsymbol{x}$ as independent variables. The estimated parameters $\widehat{\boldsymbol{\beta}}$ are used to predict values for y in the non-aware subsample. Averages of these predicted values determine ATE, ATE_1, and ATE_0, respectively,

$$\widehat{ATE} = \frac{1}{N}\sum\nolimits_{i=1}^{N} g(\boldsymbol{x_i}, \widehat{\boldsymbol{\beta}}), \tag{2}$$

$$\widehat{ATE}_1 = \frac{1}{N_e}\sum\nolimits_{i=1}^{N} w_i g(\boldsymbol{x_i}, \widehat{\boldsymbol{\beta}}), \text{ and} \tag{3}$$

$$\widehat{ATE}_0 = \frac{1}{N - N_e}\sum\nolimits_{i=1}^{N} (w_i - 1) g(\boldsymbol{x_i}, \widehat{\boldsymbol{\beta}}), \tag{4}$$

where N is the full sample number and N_e is the aware subsample number.

Estimation can be performed in a two-stage procedure. In the first stage, awareness must be accounted for because it is not random. The first stage estimates the determinants of awareness and predicts propensity scores. This is followed by the second stage, which represents the actual ATE estimation (Diagne and Demont 2007).

One interesting feature of the CI assumption is that it does not require the covariates that determine awareness and adoption to be exogenous (Diagne and Demont 2007; Kabunga et al. 2012a). 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 awareness "treatment". We will discuss this issue further below and will carry out related robustness checks.

Data and Descriptive Statistics

Survey

A household survey was conducted in the eastern and northern zones of Tanzania in late 2010. These two zones represent two main agroecological climates of Tanzania, highlands (north) and lowlands (east). Within these two zones, four districts (Mvomero, Kilosa, Karatu, and Mbulu) from three regions (Morogoro, Arusha, and Manyara) were chosen because they are major maize-producing locations; 30 wards were then selected. The number of wards per district was selected proportional to the district's total number of wards. In each district, we selected the wards with the largest maize areas. In these wards, 62 villages were randomly selected proportional to the total number of villages. At the village level, households were sampled randomly, taking district level population sizes into account. This random sampling was done using complete lists of households maintained by the village administrators. In each zone (henceforth to be referred to as "region") 350 households were selected, resulting in a total sample size of 700 households. Out of these, 695 households grew maize. The sample is not nationally representative, but it is representative of the main maize-growing areas in two regions that represent the two principal agroecological climates of Tanzania.

The head of each household was taken through a structured interview and asked to provide detailed information on household composition, location and infrastructure, social capital, asset ownership, agricultural production, and other economic activities. Agricultural production details refer to the 2008/2009 season. Input and output data for cropping activities were captured for all plots on a farm, so that the number of plot observations is larger than the number of households surveyed. With respect to varietal awareness, each farmer was asked to name the traditional varieties, improved OPVs, and hybrids they were aware of, and whether they had adopted these varieties and hybrids in 2008/2009 or before.

Descriptive Statistics

The average farm size in the sample is around five acres. This is in line with census data from Tanzania. Of all maize growers, 30% used maize hybrids on at least part of their total maize area, while 9% were partial adopters, and 21% were full adopters in 2008/2009. Both partial and full adopters are counted as adopters in our analysis. Adoption patterns differ between regions. In the north, partial adoption was observed for 14% and full adoption for 34%, whereas in the east, partial and full adoption was observed for only 5% and 8%, respectively. Considering the total maize area of farms, 23% was cultivated with hybrids. This includes recycled hybrids, which were grown on almost one-quarter of the total hybrid area.[4] All hybrids used by sample farmers were of private origin, and all seeds of private origin were hybrids (all improved OPVs were of public origin). In our analysis, we focus on hybrids because their release in Tanzania is more recent, and their expected yield potential is higher than for OPVs.[5] Following seed market liberalization in the early-1990s, over 20 hybrids were released by several seed companies. In our sample, five hybrids are most commonly used; their relative importance is similar in the north and east.

Descriptive statistics are shown in tables 2 and 3. We categorize farmers according to hybrid awareness and adoption status and compare several variables of interest. Overall, 430 farmers (62% of all maize farmers in the sample) have heard about at least one hybrid, meaning that they were aware of hybrid technology (table 2).[6] We also asked farmers more generally whether they had received information on new maize varieties before the 2008/2009 season from formal sources such as governmental or non-governmental organizations (NGOs), or private companies.[7] The share is somewhat larger among the aware farmers.

The distance to the nearest seed dealer (measured in walking time) is somewhat larger for the farmers who were aware of hybrids, which is surprising. One would have expected the opposite, but distance alone may not be a perfect proxy for access to relevant information. Information flows may also

[4] *Breeders generally advise against recycling hybrids, as the hybrid vigor decreases with each generation. However, here we want to reflect actual and conscious decisions that farmers make regarding the use of hybrids, so we include recycled hybrids in the adoption analysis. Occasionally, farmers may also grow recycled hybrids without knowing that they are hybrids; such farmers are not included in the group of adopters.*

[5] *Similar analyses could also be carried out for improved OPVs developed and distributed by the public sector. Combining both hybrids and improved OPVs to analyze the adoption of "improved seeds" more broadly would mask interesting aspects due to different conditions of diffusion for proprietary hybrids.*

[6] *Farmers were asked in the survey to list all improved maize varieties they were aware of. Further details on the source or content of the information were not collected.*

[7] *This variable is different from the hybrid awareness variable, as new varieties involve both improved OPVs and hybrids. Moreover, farmers may know hybrids without having received this information from formal sources. Fellow farmers are an important source of information in the local context.*

Table 2 Descriptive Statistics by Hybrid Awareness Status

	Aware	Unaware	Statistical significance
Information received on new varieties (dummy)	0.39	0.34	*
	(0.49)	(0.47)	
Distance to seed dealer (walking minutes)	145.05	128.98	**
	(122.72)	(100.67)	
Network member (dummy)	0.32	0.26	*
	(0.47)	(0.44)	
Village size (number of households)	645.47	595.11	**
	(255.91)	(310.00)	
Mobile phone owner (dummy)	0.44	0.39	*
	(0.50)	(0.49)	
Muslim (dummy)	0.10	0.34	***
	(0.30)	(0.47)	
Household size (number of members)	5.77	5.24	***
	(2.42)	(2.32)	
Land owned (ha)	5.01	5.52	
	(7.20)	(5.75)	
Education of farmer (years)	5.51	4.84	***
	(3.14)	(3.27)	
Age of farmer (years)	43.5	47.58	***
	(15.09)	(14.36)	
Maize experience of farmer (years)	18.82	21.06	**
	(12.31)	(15.33)	
Male household head (dummy)	0.83	0.73	***
	(0.38)	(0.44)	
North (dummy)	0.69	0.18	***
	(0.46)	(0.39)	
Number of households	430	265	

*Note: Asterisks *, **, and *** indicate that mean values are significantly different at the 10%, 5%, and 1% levels, respectively (*t*-test for continuous variables and test of equal proportions for dummy variables). Mean values are shown with standard deviations in parentheses.*

occur through social networks. We use network membership, defined as a dummy that takes a value of one if the farmer is member in any association. We consider both formal associations, such as input or marketing cooperatives, and informal associations, such as savings and credit groups. Table 2 shows that such network membership is higher among the farmers who were aware of hybrid maize technology. Aware farmers also tend to live in larger villages; village size is often positively associated with social interaction and information exchange (Matuschke and Qaim 2009). Moreover, we observe a positive correlation between awareness and ownership of a mobile phone (land lines are almost nonexistent in the study regions). In terms of land holdings, there are no significant differences between the two groups, but we do observe differences for farmer education, age, gender, and household size. Finally, the comparisons in table 2 reveal significant regional differences in awareness: 69% of all aware farmers are located in the north, 82% of all unaware farmers are located in the east.

Table 3 compares adopters and nonadopters of hybrid maize technology; it only considers the 430 aware farmers, as awareness is a necessary

Table 3 Descriptive Statistics by Hybrid Adoption Status among the Aware

	Adopter	Nonadopter	Statistical significance
Information received on new varieties (dummy)	0.44	0.34	**
	(0.50)	(0.47)	
Distance to seed dealer (walking minutes)	136.41	153.60	*
	(102.57)	(139.57)	
Network member (dummy)	0.36	0.27	**
	(0.48)	(0.45)	
Village size (number of households)	668.09	623.06	**
	(248.71)	(261.49)	
Mobile phone owner (dummy)	0.51	0.38	***
	(0.50)	(0.49)	
Muslim (dummy)	0.06	0.14	***
	(0.23)	(0.35)	
Household size (number of members)	6.01	5.52	**
	(2.44)	(2.38)	
Land owned (ha)	4.65	5.37	
	(5.04)	(8.85)	
Education of farmer (years)	5.78	5.24	**
	(3.16)	(3.11)	
Age of farmer (years)	44.32	42.68	
	(13.91)	(16.17)	
Maize experience (years)	19.25	18.40	
	(11.96)	(12.67)	
Male household head (dummy)	0.79	0.86	**
	(0.41)	(0.35)	
North (dummy)	0.80	0.59	***
	(0.40)	(0.49)	
Credit constraint (dummy)	0.23	0.21	
	(0.42)	(0.41)	
Number of households	214	216	

*Note: Asterisks *, **, and *** indicate that mean values are significantly different at the 10%, 5%, and 1% levels, respectively (t-test for continuous variables and test of equal proportions for dummy variables). Mean values are shown with standard deviations in parentheses.*

condition for adoption. About half of these aware farmers are hybrid adopters, suggesting that awareness alone is not a binding constraint to adoption for many farmers. The comparison reveals differences that are similar to those between the aware and unaware farmers. Adopters are more likely to have received information on new varieties, be network members, live in larger villages, own a cell phone, live in larger households, and have more education. Among the aware farmers, 80% of the adopters and 59% of the nonadopters are located in the north.

Unlike awareness, nonadoption is positively correlated with distance to the nearest seed dealer, which one might explain by the higher transportation costs necessary to obtain seed and related inputs. However, seed is typically purchased in small quantities only once per season, and the use of inputs such as fertilizer and pesticides is rare in our sample. Therefore, distance to seed dealer may not be a constraint to adoption as such, but a correlate of other relevant variables such as access to information. The size of landholdings is not significantly different between adopters and nonadopters. Hence, land ownership, which is one indicator of wealth, does not seem to drive adoption. Likewise, there is no difference in the share of farmers that were credit constrained. The credit constraint dummy takes a value of one if a farmer reported an unmet need for credit to buy seeds.

In summary, aware and adopting farmers tend to have more access to information as measured by several variables related to social networks and communication. At the same time, asset ownership and credit constraints do not play important roles. Against this background one could believe that nonadoption is mainly driven by information constraints, which seem to be more severe in the east. Based on this belief, policies targeted at helping farmers would focus on spreading information and raising awareness. In the next section we will examine these relationships more closely using the ATE framework.

Estimation Results

We wish to determine whether limited information is an important constraint to hybrid maize adoption in Tanzania. We therefore ask whether a lack of awareness of hybrids is the major reason for many farmers not to adopt. To accomplish this we use the ATE framework to (*a*) examine the role of several factors in determining awareness and adoption, and (*b*) predict adoption rates under complete awareness. We use the variables described in the previous section as covariates in the regression models. Credit constraint is only used in the adoption model because it is unlikely to influence awareness.[8] In the ATE framework with the CI assumption, covariates in the awareness and adoption models are allowed to differ.

Determinants of Awareness and Adoption

Table 4 shows the estimated coefficients for the hybrid awareness and awareness-corrected adoption models. Strikingly, none of the variables related to information, communication, and social networks has a significant effect on either awareness or adoption. Characteristics of the household head are also insignificant in both models, with the exception of gender. Being male increases the likelihood of hybrid awareness but reduces the likelihood of adoption. This is similar to results from Kabunga et al. (2012a), who found that female farmers are more likely to adopt technologies when disadvantages in information access are controlled for. The common conception is that women are less likely to adopt new technologies (Doss and Morris 2001), but this idea is based on research that does not differentiate between awareness and adoption.[9]

The contextual variables are also insignificant, except for the district dummies. The reference district is Karatu, which is located in the north of the country. Mbulu farmers are more likely to be aware of hybrids but less likely to adopt. For eastern farmers in Mvomero and Kilosa, the likelihood

[8] *An indirect effect is possible when credit-constrained farmers are discouraged from actively seeking information about more expensive seed options, including hybrids. As a robustness check we also included credit constraint in the awareness model, which hardly influenced the results.*

[9] *One other farmer characteristic that we tested in the adoption model is past adoption of hybrids, which led to a positive and significant coefficient. However, as past adoption is endogenous, we decided not to include this variable in the model shown in table 4.*

Table 4 Determinants of Awareness and of Awareness-corrected Adoption

	Awareness	**Adoption**
Information received on new varieties (dummy)	0.07	0.10
	(0.12)	(0.14)
Distance to seed dealer (walking minutes)	0.001	−0.001
	(0.0005)	(0.001)
Network member (dummy)	0.16	0.03
	(0.13)	(0.14)
Mobile phone owner (dummy)	0.01	0.23
	(0.12)	(0.14)
Village size (number of households)	0.0002	−0.0002
	(0.0002)	(0.0003)
Muslim (dummy)	−0.24	−0.37
	(0.15)	(0.26)
Household size (number of members)	−0.01	0.01
	(0.03)	(0.03)
Land owned (ha)	0.002	0.01
	(0.01)	(0.01)
Education of farmer (years)	0.03	0.02
	(0.02)	(0.02)
Age of farmer (years)	−0.03	0.01
	(0.03)	(0.01)
Age squared	0.0002	−0.0001
	(0.0003)	(0.0001)
Male household head (dummy)	0.32**	−0.37**
	(0.14)	(0.18)
Maize experience of farmer (years)	−0.001	−0.001
	(0.01)	(0.02)
Maize experience squared	−0.0001	−0.0001
	(0.0002)	(0.0004)
Credit constraint (dummy)		0.01
		(0.16)
Mbulu (dummy)	0.58***	−0.56***
	(0.20)	(0.18)
Mvomero (dummy)	−1.17***	−0.70**
	(0.19)	(0.28)
Kilosa (dummy)	−1.11***	−0.97***
	(0.16)	(0.21)
Number of observations	695	430
Pseudo R^2	0.25	0.10
LR chi^2 (prob > chi^2)	235.10***	57.64***
Log likelihood	−344.41	−269.23

*Note: Asterisks ** and *** indicate that coefficient is statistically significant at the 5% and 1% levels, respectively. Coefficient estimates are shown with standard errors in parentheses. The reference district is Karatu.*

of awareness and adoption is strongly reduced. Hybrids are much more widespread in the north than in the east; the question is why?

We can gain further insights by estimating the determinants separately for the north and east. Such disaggregation is useful, as it allows us to predict awareness-corrected adoption gaps separately for the two regions. This is of interest because agroecological and social conditions are different in the northern highlands and eastern lowlands. Furthermore, if the expected returns to adoption vary by region, one could also expect differences in the determinants of awareness and adoption.

Estimation results for the regional models are shown in table 5. In the awareness model for the north, several variables now turn significant: information received on new varieties from formal sources, network membership, and village size increase the likelihood of awareness (column 1). This suggests that information about hybrids spreads through formal channels (external agents) and social networks within villages. In the awareness model for the east, we see that the same three variables are not significant (column 3). If farmers receive information on new varieties through formal sources, they are not more likely to become aware of hybrids, possibly because these external agents focus on improved OPVs. The insignificance of the other two variables suggests that farmer-to-farmer information transfer does not increase awareness of hybrids either. If some farmers know or have experimented with hybrids without realizing any clear benefits, they may not further disseminate that awareness in the village and in farmer groups. This is consistent with the idea that returns to adoption are significant in the north and insignificant in the east, an issue we will inspect further below.

In the regional adoption models, a few variables also turn significant, but mostly with different effects in the north and east (columns 2 and 4 of table 5). In the north, education increases the likelihood of adoption, while the same effect is not observed in the east. Experience in maize cultivation and male household head decrease the likelihood of adoption in the east, while these effects are not observed in the north. Being Muslim also has a large negative effect on adoption in the east, possibly due to unobserved cultural or economic correlates of religion. These patterns are consistent with potential differences in returns to adoption. For example, it is often observed that experience positively predicts adoption, but in our case the opposite is true in the east. If returns to hybrid adoption are low in the east, more experienced farmers may be better equipped to make the right decision not to adopt.

Finally, two other variables deserve attention. Landholdings and credit constraints are not significant in any of the models, despite the fact that hybrid seeds are more costly than OPVs. Hence, nonadoption is unlikely to be the result of market failures relating to rural finance. One potential reason is that cash is not only required for hybrids; non-hybrids also comprise seeds that are purchased. Other possible reasons are that seed costs are not significant, or that farmers face few difficulties setting aside cash for seed purchases.

Predicted Adoption Rates under Full Awareness

We use the ATE estimates to predict adoption rates with and without information constraints for the total sample and separately by region. The results are shown in table 6. The lower part of the table shows the actually observed awareness and adoption rates, while the upper part shows predicted adoption rates when complete awareness is assumed. The JAA is identical to the observed adoption rate, while ATE_1 is identical to the observed adoption rate among the aware farmers. Of particular interest is ATE, which is the predicted adoption rate with complete awareness. The ATE for the total sample is 45%, which is 14 percentage points higher than the actual adoption rate of 31%. These 14 percentage points are explicitly stated in the GAP.

Table 5 Determinants of Awareness and of Awareness-corrected Adoption, by Region

	North		East	
	(1) Awareness	(2) Adoption	(3) Awareness	(4) Adoption
Information received on new varieties	0.58***	0.14	−0.21	0.08
	(0.21)	(0.16)	(0.16)	(0.30)
Distance to seed dealer	0.001	−0.0003	0.001	−0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Network member	0.43*	0.13	0.08	−0.28
	(0.23)	(0.17)	(0.18)	(0.31)
Mobile phone owner	−0.22	0.28	0.09	0.29
	(0.22)	(0.17)	(0.16)	(0.29)
Village size	0.001*	0.0001	0.0001	−0.0004
	(0.0004)	(0.0004)	(0.0002)	(0.0004)
Muslim	−0.56		−0.23	−0.63**
	(0.71)		(0.16)	(0.30)
Household size	0.03	−0.03	−0.06*	0.09
	(0.04)	(0.03)	(0.04)	(0.07)
Land owned	0.04	0.01	−0.02	−0.01
	(0.03)	(0.02)	(0.02)	(0.03)
Education of farmer	0.03	0.06**	0.03	−0.06
	(0.03)	(0.03)	(0.03)	(0.05)
Age of farmer	−0.01	0.01	−0.07*	0.05
	(0.01)	(0.01)	(0.04)	(0.07)
Age squared	0.00001	−0.000001	0.001	−0.001
	(0.0001)	(0.0001)	(0.0004)	(0.001)
Male household head	0.61**	−0.26	0.25	−0.71**
	(0.22)	(0.22)	(0.18)	(0.33)
Maize experience of farmer	−0.03	0.04	0.03	−0.12**
	(0.03)	(0.02)	(0.03)	(0.05)
Maize experience squared	0.0004	−0.001*	−0.001	0.003**
	(0.0005)	(0.0004)	(0.001)	(0.001)
Credit constraint		−0.14		0.24
		(0.19)		(0.32)
Mbulu / Kilosa	0.77***	−0.40**	0.05	−0.47
	(0.25)	(0.20)	(0.16)	(0.30)
Number of observations	345	295	348	132
Pseudo R^2	0.18	0.09	0.06	0.12
LR chi^2 (prob > chi^2)	50.70***	36.60***	27.90**	20.42
Log likelihood	−113.82	−183.32	−217.03	−73.10

*Note: Asterisks *, **, and *** indicate that coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively. Coefficient estimates are shown with standard errors in parentheses. The variable Muslim had to be excluded in column 2 because there are only two aware Muslim farmers in the sample who are both adopters. Mbulu refers to columns 1 and 2, where the reference district is Karatu. Kilosa refers to columns 3 and 4, where the reference district is Mvomero.*

Looking at the two regions separately, the adoption gap in the north is −0.08. Hence, hybrid adoption would increase from 49% to 57% if all farmers were aware instead of the observed 86% awareness rate. This increase in adoption through lifting information constraints is not very large; the reason is that awareness in the north is already widespread. Nevertheless, more than half of the unaware farmers in the north would adopt if they were aware. In

Table 6 Predicted Hybrid Adoption Rates

	Total	**North**	**East**
ATE-corrected population estimates			
Predicted adoption rate in the full population (ATE)	0.45***	0.57***	0.35***
	(0.02)	(0.03)	(0.04)
Predicted adoption rate in aware subpopulation (ATE_1)	0.50***	0.57***	0.33***
	(0.02)	(0.03)	(0.04)
Predicted adoption rate in unaware subpopulation (ATE_0)	0.38***	0.60***	0.37***
	(0.04)	(0.04)	(0.04)
Joint awareness and adoption rate (JAA)	0.31***	0.49***	0.12***
	(0.01)	(0.02)	(0.01)
Population adoption gap (GAP)	−0.14***	−0.08***	−0.23***
	(0.01)	(0.01)	(0.03)
Population selection bias (PSB)	0.04***	−0.004	−0.03*
	(0.01)	(0.004)	(0.02)
Observed sample estimates			
Awareness rate (N_e/N)	0.62***	0.86***	0.38***
	(0.02)	(0.02)	(0.03)
Adoption rate (N_a/N))	0.31***	0.49***	0.12***
	(0.02)	(0.03)	(0.02)
Adoption rate among the aware subsample (N_a/N_e)	0.50***	0.57***	0.33***
	(0.03)	(0.03)	(0.05)

*Note: Asterisks * and *** indicate that the estimate is statistically significant at the 10% and 1% levels, respectively. Estimates are shown with standard errors in parentheses.*

the east, the adoption gap due to information constraints is −0.23, suggesting that the adoption rate would increase from 12% to 35% with full awareness. This increase is larger than in the north, because awareness about hybrids is less widespread in the east. On the other hand, only one-third of the unaware farmers in the east would adopt if they were aware.

The welfare impacts of closing the adoption gap are not necessarily positive for all farmers. Using the same data from maize farmers in Tanzania, Kathage et al. (2012) showed that hybrids are much higher yielding than nonhybrids in the north, but that there are no significant yield differences in the east. Kathage et al. (2012) also estimated maize production functions, controlling for other inputs as well as farm and household characteristics. The estimates confirm that the net hybrid yield impact is large and significant in the north but not in the east. Differential impacts are due to diverse agroecological conditions in the two regions. While the range of available hybrids is similar in both regions, these available hybrids are better suited to the higher altitudes in the north.[10] Hence, increased hybrid awareness and adoption may increase farmers' welfare in the north, but less so in the east. Although hybrid awareness may only represent an initial stage of knowledge, it is possible that increased efforts to raise the awareness of existing hybrids among farmers in the east could be a waste of resources.

[10] *Against this background it is unclear why a few farmers in the east nevertheless adopted hybrids. First, there is some heterogeneity in agroecological conditions also within regions, so it is possible that individual farmers benefit from adoption even when the mean yield effect is insignificant. Second, adopters in the east may still be in the process of experimenting with hybrids and might disadopt in the future. Third, it is possible that some farmers see advantages in hybrid adoption other than yield gains. Unfortunately our data does not allow us to analyze this in more detail.*

Robustness Checks

In the analytical framework section we discussed that—under the CI assumption, which holds in the adoption context—the covariates used in the awareness and adoption models do not have to be exogenous. In fact, predicting the effect of awareness on adoption is feasible even if all covariates are endogenous (Diagne and Demont 2007). The only requirement is that their values are unaffected by the awareness "treatment". This can safely be assumed for most of the variables we used, as general farm and household characteristics are not influenced by the awareness of hybrid maize. However, for three variables in particular the issue is not so clear, namely network membership, information received on new varieties, and ownership of a mobile phone. It is at least possible that individual social networks and information sources change when farmers learn about a new technology and start to adopt. To test whether this may introduce any bias to our results, we re-estimated all models without including these three variables (network member, information received on new varieties, mobile phone owner). The estimation coefficients of the other variables hardly change in these alternative specifications. Nor do the predictions of population adoption rates and adoption gaps change significantly. The results of these robustness checks are shown in table A.1 in the appendix. The predictions are almost identical to those in table 6. We conclude that the estimates discussed above do not suffer from endogeneity bias.

Conclusions

We have examined whether information is an important constraint to hybrid maize adoption in Tanzania, or what other factors could explain the relatively low adoption rates. Using the average treatment effect framework and primary survey data from two regions, we found that variables related to information and communication do not significantly influence technology awareness or adoption in the aggregate model. Regionally disaggregated models showed that some of these variables were significant in the north, where returns to adoption are large, but most of the farmers in the north are already aware of hybrid technology. The adoption gap due to information constraints is small for the north and larger for the east. However, hybrids do hardly increase yields in the east.

Limited information is not the only possible constraint to technology adoption. Low levels of asset ownership, which are typically associated with higher risk aversion, and lack of access to credit are often mentioned as other factors (Foster and Rosenzweig 2010). Moreover, low availability of seeds in remote areas can play a role when infrastructure conditions are poor. All these factors can contribute to adoption gaps in general, but in our case they do not seem to explain the low hybrid adoption rates in the east. Neither information related factors nor variables measuring asset ownership and credit constraints were significant in the east. Even if we did not measure all factors very precisely, the main conclusion seems robust: a lack of awareness is not the root cause of low adoption. Rather, differences in adoption returns may explain why both awareness and adoption are much lower in the east than in the north.

Our results imply that, especially when technology adoption and awareness rates are low, one should not automatically infer that constraints are preventing farmers from adopting. This finding has some policy implications. As development budgets are limited, investment options should be scrutinized in terms of their efficiency in achieving stated goals. If the goal is increasing smallholder productivity, resources must be allocated between improving access to existing technologies and creating new technologies. One set of constraints relates to imperfect information. Farmers may simply not be aware of existing technologies and their benefits, so they do not adopt. However, in some situations low awareness and adoption could also be explained by low returns. In that case, efforts to improve awareness and remove other (nonbinding) constraints are misguided and might even be harmful if the net benefits of a technology are negative. For hybrid maize in Tanzania, we have shown that raising awareness could increase adoption somewhat, yet without improving productivity for many farmers. Therefore, money would be more wisely spent on developing seeds better suited to diverse local conditions.

To draw some broader lessons about the role of information for adoption, it is useful to differentiate between different types of technologies. Improved crop varieties are often relatively easy to use, without the need for much site-specific experimentation and adaptation by farmers. For such easy-to-use technologies, information spreads relatively fast when these technologies are beneficial. Hence, awareness is positively correlated with benefit potential. In that case, an adoption gap may not primarily require improvements in information flows. This can be different for more knowledge-intensive technologies that require site-specific adaptation, as holds true for many natural resource management technologies (Noltze et al. 2012). In such cases, a farmer-to-farmer transfer of information is less straightforward, and being aware of a technology alone may not suffice for successful adoption. For knowledge-intensive technologies, it may be useful to differentiate between awareness and knowledge, as was done by Kabunga et al. (2012a). An adoption gap due to limited knowledge may require improvements in information flows, for instance through more effective extension services.

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Appendix

Table A1. Predicted Hybrid Adoption Rates (Reduced Specification)

	Total	**North**	**East**
ATE-corrected population estimates			
Predicted adoption rate in the full population	0.45***	0.57***	0.35***
(*ATE*)	(0.02)	(0.03)	(0.04)
Predicted adoption rate in aware subpopulation	0.50***	0.57***	0.33***
(ATE_1)	(0.02)	(0.03)	(0.04)
Predicted adoption rate in unaware	0.38***	0.62***	0.37***
subpopulation (ATE_0)	(0.04)	(0.04)	(0.04)
Joint awareness and adoption rate (*JAA*)	0.31***	0.49***	0.12***
	(0.01)	(0.02)	(0.01)
Population adoption gap (*GAP*)	−0.14***	−0.09***	−0.23***
	(0.01)	(0.01)	(0.03)
Population selection bias (*PSB*)	0.04***	−0.01	−0.02
	(0.01)	(0.004)	(0.01)
Observed sample estimates			
Awareness rate (N_e/N)	0.62***	0.86***	0.38***
	(0.02)	(0.02)	(0.03)
Adoption rate (N_a/N))	0.31***	0.49***	0.12***
	(0.02)	(0.03)	(0.02)
Adoption rate among the aware subsample	0.50***	0.57***	0.33***
(N_a/N_e)	(0.03)	(0.03)	(0.05)

*Note: Asterisks * and *** indicate that estimate is statistically significant at the 10% and 1% levels, respectively. Estimates are shown with standard errors in parentheses. The specification here excludes the variables information received on new varieties, network membership, and mobile phone ownership.*