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RTG 1666 GlobalFood

Transformation of Global Agri-Food Systems:
Trends, Driving Forces, and Implications for Developing Countries

Georg-August-University of Göttingen

GlobalFood Discussion Papers

No. 19

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Feburary 2013

RTG 1666 GlobalFood · Heinrich Düker Weg 12 · 37073 Göttingen · Germany
www.uni-goettingen.de/globalfood

ISSN (2192-3248)

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

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Abstract: Modern technologies are often not widely adopted among smallholder farmers in Sub-Saharan Africa. Several adoption constraints have been discussed in the literature, including limited access to information. Using survey data from farmers in Tanzania and the average treatment effect framework, we question the hypothesis that limited information is an important constraint for the adoption of hybrid maize technology. While we find an adoption gap from incomplete awareness exposure, this gap is sizeable only in the east of Tanzania, where productivity effects of hybrids are small. In the north, where adoption is much more beneficial, almost all farmers are already aware of hybrids. The results suggest that exposure to a new technology may be a function of expected returns to adoption. We also test for other constraints related to credit and risk, which do not determine adoption significantly. More generally, nonadoption of technologies is not always a sign of constraints but may also indicate low benefits. Some policy implications are discussed.

Key words: farm survey, technology adoption, hybrid maize; Tanzania

JEL codes: O13, O33, Q12, Q16

Acknowledgments: The household survey for this research was financially supported by the Australian Center for International Agricultural Research (ACIAR) under the CIMMYT led project Sustainable Intensification of Maize-Legume Cropping Systems in Eastern and Southern Africa (SIMLESA).

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1 Introduction

Agricultural technology is a fundamental driving force for rural development. But the adoption 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 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 availability alone (Byerlee and Heisey, 1996). 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 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 pointed towards behavioral biases as a related but conceptually different set of constraints (Duflo et al., 2011). Farmers may have access to information, credit, and insurance, but fail to behave rationally, for example by discounting myopically. 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 with a view to facilitating innovation adoption and productivity growth.

In this article, we analyze the adoption of hybrid maize technology in Tanzania, testing the different possibilities. Maize is the main staple food in Tanzania and is primarily grown by smallholder farmers. We use survey data from two regions, the north where hybrid adoption rates are relatively high, and the east where adoption is much lower. Specifically, we examine whether low adoption can be explained by lack of awareness exposure, and whether low adoption and lack of exposure may be the result of limited returns. To our knowledge, such a link between information constraints and returns to adoption has never been analyzed in the empirical literature. We use Diagne and Demont's (2007) average treatment effect (ATE) framework to show that lack of awareness of hybrid seeds is not an important constraint to adoption in Tanzania. The adoption gap caused by incomplete awareness is not very large. And, assuming full exposure, adoption rates would still differ considerably between the two regions, which we explain by insignificant yield effects of hybrid technology 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 exposure may actually be a function of expected returns. We do not find evidence for constraints related to risk or credit and conclude that the alleviation of adoption constraints with respect to existing technologies should be carefully balanced with efforts to develop new technologies that are better targeted to diverse local conditions.

2 Background

There are multiple and sometimes conflicting reasons mentioned for the low adoption rates of MVs in Sub-Saharan Africa. One explanation is that available MVs are not sufficiently adapted to local farmers' needs (Doss, 2003). Byerlee and Heisey (1996) argue that breeders have paid too little attention to local agroecological conditions, agronomic practices, processing characteristics, and seasonal labor availability. Smale et al. (1995) show for Malawi that many MV adopters continue to use traditional varieties due to consumption preferences and that they allocate less land to MVs with lower market orientation. Feleke and Zegeye (2006) observe for Ethiopia that MV adoption is more likely with higher labor availability. Suri (2011) uses a model that allows for heterogeneity in profitability and finds that many Kenyan farmers did not adopt hybrids because of limited benefits. However, she 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.

Such infrastructure constraints, including poor market integration, communication, and transport, comprise a second cluster of explanatory factors (Chirwa, 2005). Women in particular often face difficulties in accessing inputs that are complementary to MVs (Doss and Morris, 2001). 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) confirm that credit club membership increases the likelihood of adoption of MVs and fertilizers.

In contrast, Duflo et al. (2008) maintain that low fertilizer and hybrid seed adoption can be explained by non-fully rational behavior, rather than by low returns or exogenous constraints. Based on randomized controlled trials, they posit that farmers have trouble in learning whether fertilizer recommendations are adapted to their conditions and struggle to save enough money for buying seeds and other inputs in the next planting season. Duflo et al. (2011) suggest that simple interventions ("nudges"), such as improving the information provided by extension agents, could help; they also report that when farmers are offered to buy fertilizer at the end of the previous season, adoption rates increase significantly. Improving extension services could also reduce the apparent lack of farmers' awareness of improved MVs (Langyintuo et al., 2010). Also referring to extension services, Spielman et al. (2010) attribute low adoption levels partly to inflexible one-size-fits-all recommendations.

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 superiority of the new 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. Second, 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". Third, due to vested interests or ignorance, seed companies and/or government extension services may delude farmers into adopting inferior varieties that do not benefit them, with farmers having little understanding and control of this process. In that case, biases in the information delivered to farmers must be overcome, and new varieties better adapted to local conditions be made available. Fourth, traditional varieties may be superior to MVs for many farmers, 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 varieties that are better adapted to farmers' conditions.

[Table 1]

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 active social networks can reduce such hurdles. Kabunga et al. (2012a, 2012b) have analyzed the adoption of tissue culture (TC) bananas in Kenya, which is a relatively knowledge-intensive technology. While most farmers are aware of this technology, many do not know how to use TC successfully, so that 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 hardly 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 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 larger. 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 Bt 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 to reach additional customers. Information about successful technologies will also spread through word-of-mouth. For example, Matuschke and Qaim (2008) observed that hybrid adopters with positive experiences are important sources of information for other farmers. Conversely, one can expect that highly negative impacts of a technology will also become a warning to others, while insignificant impacts may not be reported and noticed widely.

3 Analytical Framework

In order to analyze information constraints to hybrid adoption we use the ATE framework, which goes back to the work of Rubin (1973). It was applied in a technology adoption context by Diagne and Demont (2007), and more recently by Kabunga et al. (2012a). We follow this approach and summarize the relevant details in the following.

Diagne and Demont (2007) demonstrate that the “true” population adoption rate cannot be consistently estimated unless exposure is controlled for. The “true” adoption rate refers to a situation of complete exposure to a technology. The adoption rate observed in a sample from a population that is not completely exposed is lower, since at least some of the nonexposed farmers would adopt if they were exposed (Diagne and Demont, 2007). Nor can the true population adoption rate be estimated consistently from the subsample of exposed farmers due to selection bias in exposure. Also the determinants of adoption cannot be estimated consistently, unless they are separated from the determinants of exposure. A farmer cannot decide whether to adopt a technology when not aware of it. For example, if social networks are found to have an impact on adoption, we do not know whether social networks matter for exposure, adoption, or both. But knowing this matters for the design of policy interventions.

The ATE framework is used to separate exposure and adoption and to calculate adoption gaps resulting from incomplete exposure. The two main components of this framework are a binary treatment variable w that refers to exposure 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 exposed and adoption status if not exposed (y_{1i} - y_{0i}). It corresponds to $E(y_{1i} - y_{0i})$ at the population level, where it is called *ATE*. y_{0i} is always equal to zero, since exposure is a necessary condition for adoption. Therefore, *ATE* reduces to $E(y_{1i})$. For exposed farmers, y_{1i} is observed and called the average treatment effect on the treated (ATE_1). For nonexposed 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 exposure and adoption rate (*JEA*), because observed adoption implies exposure. The difference between *JEA* and *ATE* is called the adoption gap (*GAP*). *GAP* indicates by how much incomplete exposure 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 exposure based on the observed adoption rate among the exposed subsample.

The challenge of identifying *ATE* amounts to estimating y_{1i} for the nonexposed subsample. The identification of *ATE* is based on the conditional independence assumption (CI), which states that treatment status w is independent of potential outcome status y conditional on a set of observed covariates z: $P(y_j = 1 \mid w, z) = P(y_j = 1 \mid z)$; $j = 0, 1$. The *ATE* estimators based on the CI assumption can be estimated using either parametric or nonparametric regression methods. Following Kabunga et al. (2012a), we employ parametric regression in a model for the conditional expectation of the observed variables y, x, and w (for details see Demont and Diagne, 2007):

$$E\,(y \mid x, w = 1) = g(x, \beta)$$

where g is a function of observed covariates x determining adoption and a parameter vector β. The parameter vector β can be estimated by maximum likelihood techniques using observations in the exposed subsample with y as dependent and x as independent variables. The estimated parameters $\hat{\beta}$ are used to predict values for y in the nonexposed subsample. Averages of these predicted values determine ATE, ATE_1, and ATE_0, respectively:

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

$$\widehat{ATE}_1 = \frac{1}{N_e}\sum wg(x, \hat{\beta})$$

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

Exposure must be controlled for in a first stage because it is not random. This first stage, which estimates the determinants of exposure and predicts propensity scores, predates the *ATE* estimation. The covariates determining exposure (z) are allowed to differ from the covariates determining adoption (x) (Diagne and Demont, 2007).

4 Data and Descriptive Statistics

4.1 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, Mbulu) from three regions (Morogoro, Arusha, Manyara) were deliberately chosen. Then, 30 wards and 60 villages were randomly selected. At the village level, households were sampled randomly, taking district level population sizes into account. In each zone (henceforth "region") 350 households were selected, resulting in a total sample size of 700 households. Out of these, 695 grew maize.

The head of each household was taken through a structured interview, providing 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 them in 2008/2009 or before.

4.2 Descriptive Statistics

The average farm size in the sample is around 5 acres. This is in line with census data from Tanzania. Of all maize growers, 31% used maize hybrids at least on a part of their total maize area; 9% were partial adopters and 21% were full adopters in 2008/2009. 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. 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 higher than for OPVs. Following seed market liberalization in the early 1990s, over 20 hybrids have been 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 exposure 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 are exposed to hybrid technology (Table 2). We had also asked farmers more generally whether they had received information on new maize varieties before the 2008/2009 season from formal sources, such as government, non-governmental organizations (NGOs), or private companies.[1] The share is somewhat larger among the exposed farmers.

[Table 2]

The distance to the next seed dealer, measured in walking time, is somewhat larger for the exposed farmers, 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 occur through social networks. We use network membership, defined as a dummy that takes a value of one if the farmers is member in any formal or informal association ranging from input or marketing cooperatives to savings and credit groups. Table 2 shows that such

[1] This variable is different from the exposure 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.

network membership is higher among the farmers exposed to hybrid maize technology. Exposed farmers also tend to live in larger villages, which is often associated with more social interaction and information exchange (Matuschke and Qaim, 2009). Moreover, we observe a positive correlation between exposure and ownership of a cell 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 exposure: 69% of all exposed farmers are located in the north, 82% of all nonexposed farmers are located in the east.

Table 3 compares adopters and nonadopters of hybrid technology. It only considers the 430 exposed farmers, as exposure is a necessary condition for adoption. About half of these exposed 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 exposed and nonexposed 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 exposed, 80% of adopters and 59% of nonadopters are located in the north.

[Table 3]

Unlike for exposure, nonadoption is positively correlated with distance to the nearest seed dealer, which one might explain by higher transportation costs 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 more relevant variables. The size of landholdings is not significantly different between adopters and nonadopters.

Hence, asset ownership does not seem to drive adoption, and also risk may not be a major determinant (land assets provide insurance). Likewise, there is no difference in the share of farmers that were credit constrained, defined as an unmet need for credit to buy seeds.In summary, exposed 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, risk, and access to credit 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 to help farmers would focus on spreading awareness. In the next section, we will examine these relationships more closely using the ATE framework explained earlier.

5 Results

We want to know whether limited information is an important constraint to hybrid adoption in Tanzania. In other words, we ask whether lack of awareness of hybrids is the major reason for many farmers not to adopt. We use the ATE framework to: (1) examine the role of several factors in determining exposure and adoption; and (2) predict adoption rates under complete exposure. 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 exposure.

5.1 Determinants of Exposure and Adoption

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

The contextual variables are also insignificant, except for the district dummies. The reference district is Karatu, which is located in the north. Mbulu farmers are more likely to be exposed but less likely to adopt. For eastern farmers in Mvomero and Kilosa the likelihood of exposure and adoption is strongly reduced. Hybrids are much more widespread in the north than in the east, the question is why?

[Table 4]

We can gain further insights by estimating the determinants separately for north and east (Table 5). In the exposure 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 exposure (column 1). This suggests that information about hybrids spreads through formal channels (external agents) and social networks within villages. In the exposure 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 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 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.

[Table 5]

In the regional adoption models, a few variables also turn significant, but mostly with different effects in north and east (columns 2 and 4). 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. 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. Land holdings 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 credit or insurance.

5.2 Predicted Adoption Rates Under Full Exposure

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 exposure and adoption rates. The upper part shows predicted adoption rates when complete exposure is assumed. *JEA* is identical to the observed adoption rate, while ATE_1 is identical to the observed adoption rate among the exposed farmers. Of particular interest is *ATE,* which is the predicted adoption rate with complete exposure. *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 6]

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 exposed instead of the observed 86% exposure 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 nonexposed farmers in the north would adopt if they were exposed. In 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 exposure. 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 nonexposed farmers in the east would adopt if they were exposed.

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 yield models for all maize plots cultivated by sample farmers, controlling for other inputs as well as plot and household characteristics. Results from their main model are summarized in Table 7; they confirm that the net hybrid yield impact is large and significant in the north but not in the east. These differences are probably due to heterogeneous agroecological conditions, for which the region dummies are proxies. The range of available hybrids is similar in both regions, but these hybrids are better suited to the highland conditions in the north. Under these conditions in the north, increased exposure and adoption may improve farmers' welfare. However, in the east, an increase in exposure and adoption is unlikely to improve welfare significantly. Efforts to improve access to information and increase awareness of existing hybrids may represent a waste of resources there.

[Table 7]

6 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. The 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. Lack of access to credit and insurance against risk 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 data 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: limited awareness exposure is not the root cause of low adoption; rather differences in returns may explain why both exposure and adoption are much lower in the east than in the north.

Our results imply that, especially when adoption and exposure rates are low, one should not automatically infer that constraints are preventing farmers from adopting useful technologies. 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 that they do not adopt. However, in some situations low exposure 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 exposure 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 exposure 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 exposure and knowledge exposure, as was done by Kabunga et al. (2012a). An adoption gap due to limited knowledge exposure may require improvements in information flows, for instance through more effective extension services.

References

Byerlee, D., Heisey, P., 1996. Past and potential impacts of maize research in sub-Saharan Africa: A critical assessment. Food Policy 21, 255-277.

Chirwa, E., 2005. Adoption of fertiliser and hybrid seeds by smallholder maize farmers in Southern Malawi. Development Southern Africa 22, 1-12.

Diagne, A., Demont, M., 2007. Taking a new look at empirical models of adoption: Average treatment effect estimation of adoption rates and their determinants. Agricultural Economics 37, 201-210.

Doss, C., 2003. Understanding farm level technology adoption: Lessons learned from CIMMYT's micro surveys in Eastern Africa. CIMMYT Economics Working Paper 03-07. Mexico, D.F.: International Maize and Wheat Improvement Center.

Doss, C., Morris, M., 2001. How does gender affect the adoption of agricultural innovations? The case of improved maize technology in Ghana. Agricultural Economics 25, 27-39.

Duflo, E., Kremer, M., Robinson, J., 2008. How high are rates of return to fertilizer? Evidence from field experiments in Kenya. American Economic Review 98, 482-488.

Duflo, E., Kremer, M., Robinson, J., 2011. Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. American Economic Review 101, 2350-2390.

Feleke, S., Zegeye, T., 2006. Adoption of improved maize varieties in Southern Ethiopia: Factors and strategy options. Food Policy 31, 442-457.

Foster, A.D., Rosenzweig, M.R., 2010. Microeconomics of technology adoption. Annual Review of Economics 2, 395-424.

Griliches, Z., 1957. Hybrid corn: An exploration in the economics of technological change. Econometrica 25, 501-522.

Kabunga, N.S., Dubois, T., Qaim, M., 2012a. Heterogeneous information exposure and technology adoption: The case of tissue culture bananas in Kenya. Agricultural Economics 43, 473-486.

Kabunga, N.S., Dubois, T., Qaim, M., 2012b. Yield effects of tissue culture bananas in Kenya: Accounting for selection bias and the role of complementary inputs. Journal of Agricultural Economics 63, 444-464.

Kathage, J., Qaim, M., Kassie, M., Shiferaw, B., 2012. Seed market liberalization, hybrid maize adoption, and impacts on smallholder farmers in Tanzania. GlobalFood Discussion Paper 12, Goettingen: University of Goettingen.

Langyintuo, A., Mwangi, W., Diallo, A., MacRobert, J., Dixon, J., 2010. Challenges of the maize seed industry in Eastern and Southern Africa: A compelling case for private-public intervention to promote growth. Food Policy 35, 323-331.

Matuschke, I., Qaim, M., 2008. Seed market privatisation and farmers' access to crop technologies: The case of hybrid pearl millet adoption in India. Journal of Agricultural Economics 59, 498-515.

Matuschke, I., Qaim, M., 2009. The impact of social networks on hybrid seed adoption in India. Agricultural Economics 40, 493-505.

Noltze, M., Schwarze, S., Qaim, M., 2012. Understanding the adoption of system technologies in smallholder agriculture: The system of rice intensification (SRI) in Timor Leste. Agricultural Systems 108, 64-73.

Rubin, D.B., 1973. Matching to remove bias in observational studies. Biometrics 29, 159-183.

Shiferaw, B., Prasanna, B.M., Hellin, J., Bänziger, M., 2011. Crops that feed the world 6. Past successes and future challenges to the role played by maize in global food security. Food Security 3, 307-327.

Smale, M., Heisey, P., Leathers, H., 1995. Maize of the ancestors and modern varieties: The microeconomics of high-yielding variety adoption in Malawi. Economic Development and Cultural Change 43, 351-368.

Spielman, D., Byerlee, D., Alemu, D., Kelemework, D., 2010. Policies to promote cereal intensification in Ethiopia: The search for appropriate public and private roles. Food Policy 35, 185-194.

Suri, T., 2011. Selection and comparative advantage in technology adoption. Econometrica 79, 159-209.

Table 1: Adoption Behavior, Impact, Causes, and Remedies

	MVs adopted	**MVs not adopted**
MVs superior to 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 superior to MVs	3. Farmers are deluded into adopting MVs that do not benefit them. *Remedy: Improve flow of unbiased information. Develop varieties better adapted to farmers' conditions.*	4. Lack of MVs adapted to farmers' conditions is responsible for low adoption rates. *Remedy: Develop varieties better adapted to farmers' conditions.*

Source: Authors' illustration.

Table 2: Descriptive Statistics by Exposure Status

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

*, **, *** Mean value is significantly higher than that of exposed/nonexposed at the 10%, 5% and 1% level, respectively. Mean values are shown with standard deviations in parentheses.

Table 3: Descriptive Statistics by Adoption Status among Exposed

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

*, **, *** Mean value is significantly higher than that of adopter/nonadopter. Mean values are shown with standard deviations in parentheses.

Table 4: Determinants of Exposure and Exposure-corrected Adoption

	Exposure	Adoption
Information received on new varieties (dummy)	0.07 (0.12)	0.10 (0.14)
Distance to seed dealer (walking minutes)	0.001 (0.0005)	-0.001 (0.001)
Network member (dummy)	0.16 (0.13)	0.03 (0.14)
Cell phone owner (dummy)	0.01 (0.12)	0.23 (0.14)
Village size (number of households)	0.0002 (0.0002)	-0.0002 (0.0003)
Muslim (dummy)	-0.24 (0.15)	-0.37 (0.26)
Household size (number of members)	-0.01 (0.03)	0.01 (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 (0.03)	0.01 (0.01)
Age squared	0.0002 (0.0003)	-0.0001 (0.0001)
Male household head (dummy)	0.32** (0.14)	-0.37** (0.18)
Maize experience (years)	-0.001 (0.01)	-0.001 (0.02)
Maize experience squared	-0.0001 (0.0002)	-0.0001 (0.0004)
Credit constraint (dummy)		0.01 (0.16)
Mbulu (dummy)	0.58*** (0.20)	-0.56*** (0.18)
Mvomero (dummy)	-1.17*** (0.19)	-0.70** (0.28)
Kilosa (dummy)	-1.11*** (0.16)	-0.97*** (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

, * Coefficient is statistically significant at the 5% and 1% level, respectively. Coefficient estimates are shown with standard errors in parentheses. The reference district is Karatu.

Table 5: Determinants of Exposure and Exposure-corrected Adoption, by Region

	North		East	
	1	2	3	4
	Exposure	Adoption	Exposure	Adoption
Information received on new varieties	0.58*** (0.21)	0.14 (0.16)	-0.21 (0.16)	0.08 (0.30)
Distance to seed dealer	0.001 (0.001)	-0.0003 (0.001)	0.001 (0.001)	-0.002 (0.002)
Network member	0.43* (0.23)	0.13 (0.17)	0.08 (0.18)	-0.28 (0.31)
Cell phone owner	-0.22 (0.22)	0.28 (0.17)	0.09 (0.16)	0.29 (0.29)
Village size	0.001* (0.0004)	0.0001 (0.0004)	0.0001 (0.0002)	-0.0004 (0.0004)
Muslim	-0.56 (0.71)		-0.23 (0.16)	-0.63** (0.30)
Household size	0.03 (0.04)	-0.03 (0.03)	-0.06* (0.04)	0.09 (0.07)
Land owned	0.04 (0.03)	0.01 (0.02)	-0.02 (0.02)	-0.01 (0.03)
Education of farmer	0.03 (0.03)	0.06** (0.03)	0.03 (0.03)	-0.06 (0.05)
Age of farmer	-0.01 (0.01)	0.01 (0.01)	-0.07* (0.04)	0.05 (0.07)
Age squared	0.00001 (0.0001)	-0.000001 (0.0001)	0.001 (0.0004)	-0.001 (0.001)
Male household head	0.61** (0.22)	-0.26 (0.22)	0.25 (0.18)	-0.71** (0.33)
Maize experience of farmer	-0.03 (0.03)	0.04 (0.02)	0.03 (0.03)	-0.12** (0.05)
Maize experience squared	0.0004 (0.0005)	-0.001* (0.0004)	-0.001 (0.001)	0.003** (0.001)
Credit constraint		-0.14 (0.19)		0.24 (0.32)
Mbulu / Mvomero	0.77*** (0.25)	-0.40** (0.20)	0.05 (0.16)	-0.47 (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

*, **, *** Coefficient is statistically significant at the 10%, 5%, and 1% level, 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 exposed Muslim farmers in the sample who are both adopters. Mbulu refers to columns 1 and 2, the reference district is Karatu. Mvomero refers to columns 3 and 4, the reference district is Kilosa.

Table 6: Predicted Adoption Rates

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

*, *** Estimate is statistically significant at the 10% and 1% level, respectively. Estimates are shown with standard errors in parentheses.

Table 7: Yield Impact of Hybrid Maize

	Maize yield in 2008/2009 (kg/acre)
Hybrid (dummy)	0.56*** (0.12)
Hybrid-east interaction	-0.50*** (0.22)
Number of observations	1117

*** Coefficient is statistically significant at the 1% level. Coefficient estimates are shown with standard errors in parentheses. Cobb-Douglas functional form. Covariates not shown for brevity. Source: Kathage et al. (2012).