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A Case of Mistaken Identity?
Measuring Rates of Improved Seed Adoption in Tanzania Using DNA Fingerprinting

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EPAR Technical Report #363

February 10, 2019

Abstract

Studies of improved seed adoption in developing countries almost always draw from household surveys and are premised on the assumption that farmers are able to self-report their use of improved seed varieties. However, recent studies suggest that farmers' reports of the seed varieties planted, or even whether seed is local or improved, are sometimes inconsistent with the results of DNA fingerprinting of farmers' crops. We use household survey data from Tanzania to test the alignment between farmer-reported and DNA-identified maize seed types planted in fields. In the sample, 70% of maize seed observations are correctly reported as local or improved, while 16% are type I errors (falsely reported as improved) and 14% are type II errors (falsely reported as local). Type I errors are more likely to have been sourced from other farmers, rather than formal channels. An analysis of input use, including seed, fertilizer, and labor allocations, reveals that farmers tend to treat improved maize differently, depending on whether they correctly perceive it as improved. This suggests that errors in farmers' seed type awareness may translate into suboptimal management practices. In econometric analysis, the measured yield benefit of improved seed use is smaller in magnitude with a DNA-derived categorization, as compared with farmer reports. The greatest yield benefit is with correctly identified improved seed. This indicates that investments in farmers' access to information, seed labeling, and seed system oversight are needed to complement investments in seed variety development.

1. Introduction

Crop yields in sub-Saharan Africa (SSA) have long lagged behind other parts of the world, including South and Southeast Asia and Latin America (Otsuka and Muraoka 2017; Yu and Nin-Pratt 2011). Growth in staple crop production in East Africa, including maize and rice, has generally stemmed from area expansion, rather than an increase in productivity (FAO 2017, cited in Tegemeo 2017). At the same time, adoption of improved seed varieties[1] in the region is fairly low. As of 2006/07, just 33% of maize area in East Africa (and 18% in Tanzania) was cultivated with improved seed (Smale et al. 2013). As improved seed varieties are higher-yielding than local seed (or designed to be disease resistant or stress tolerant), the adoption of such seed has the potential to enhance the farming outcomes and overall welfare of farm-households (Abate et al. 2017; Alwang et al. 2018).

[1] In this paper, "improved seed" refers to seed that was originally developed in the research laboratory of a seed company or agricultural research center and released to the public. "Seed type" refers to the seed's status as being improved or local (landrace), and "seed variety" refers to the specific variety of improved or local seed.

For this reason, the literature is replete with studies of the effects of improved seed adoption on crop yield and farm-household welfare. By highlighting what is (or is not) effective, such studies capture the impacts of crop improvement research and guide what types of research might be prioritized (Floro et al. 2017; Walker and Alwang 2015). Authors overwhelmingly find that the adoption of improved seed varieties (or cuttings) and rapid varietal turnover can be welfare-enhancing in SSA (Asfaw et al. 2012; Jaleta et al. 2018; Kassie et al. 2011; Khonje et al. 2015; Kijima et al. 2008; Manda et al. 2017; Mathenge et al. 2014a; Shiferaw et al. 2014; Verkaart et al. 2017; Zeng et al. 2015), although some reach a more nuanced conclusion (Alwang et al. 2018). Many of these papers also probe the potential constraints to adoption of improved seed, ranging from challenges of access in a poorly developed seed system, to a lack of information, liquidity constraints, or a lack of access to complementary inputs. Wainaina et al. (2017) further note synergistic effects when improved seeds and agrochemical or management technologies are adopted simultaneously. These studies inform the design of policies to facilitate farmer uptake of improved seed and optimize the results of adoption.

Such studies almost always draw from household surveys and are premised on the assumption that farmers are able to self-report their use of improved seed varieties (Abate et al., 2017; Maredia et al. 2016; Walker and Alwang 2015). However, recent evidence suggests that self-reports may be unreliable, as farmers do not always correctly identify the seed type they've used (Floro et al. 2017; Kosmowski et al. 2018; Maredia et al. 2016; Rabbi et al. 2015). Misidentification of seed type, especially if widespread, can potentially skew the detected rate of adoption of improved seed, an important metric for agricultural research centers and development practitioners. Misidentification may also affect the results of studies regarding the farm-level effects of improved seed use. Depending on the research question being asked, this may lead to imprecise estimates, attenuation bias, or systematic bias if farmers' patterns of misidentification are not random (Hausman 2001). For example, if more capable and better-informed farmers are also more likely to identify improved seeds correctly, a positive correlation between improved seed use and yields could be spurious. Misidentification of seed type also has consequences for the farmers themselves if they allocate other inputs based on a false perception of what was planted, or if they make decisions regarding the adoption or dis-adoption of improved varieties based on faulty evidence.

There are several reasons why farmers may not properly identify seed type, including both misinformation and mismeasurement. Farmers could simply have a poor understanding of what constitutes an "improved" or "modern" variety (Maredia et al. 2016). Alternatively, where the formal seed system is characterized by weak oversight, supposedly improved seed may be adulterated before it is purchased from an agro-dealer or other formal seed source (Bold et al. 2017). At the time of purchase, farmers are likely unable to visually confirm the seed quality or type (Spielman et al. 2017). Quality-declared seed systems, in which smallholder farmers produce seed intended for sale within certain guidelines of quality assurance, may also be susceptible to quality lapses (intentional or not) or ineffective oversight. And inexpensive seeds sourced through the informal system—including purchases from local markets and farmer-to-farmer seed exchanges—may be misrepresented, either because sellers have simply lost track of the seed variety being exchanged, or through willful deception. As noted by Westengen et al. (2014), both local and farmer-recycled improved varieties are sourced through these informal channels.

Farmers may also be unsure of the improved status of their seed due to the loss of genetic identity in the process of recycling (Morris et al. 1999), or the "creolization" of cross-pollinating crops (Westengen et al. 2014). This occurs when improved varieties are hybridized with nearby local varieties, a phenomenon that may be either intentional (a result of farmer selection) or unintentional. Thus, farmers may feel confident of the improved status of newly-purchased seed but could express uncertainty over how future generations of seed ought to be characterized. In addition, an improved variety that was released decades ago and has been passed along through farmer exchanges may be described as "local", even as it was initially developed in a research laboratory (Kosmowski et al. 2018). A final explanation for the incorrect identification of seed type could involve farmers planting multiple seed varieties within a single field as a risk management strategy (Spielman et al. 2017), though a household survey might only collect information on the main variety used. At the level of seed variety, farmers may misidentify the specific variety if they are unfamiliar with variety names or if there is any inconsistency between the official versus locally adapted names (Floro et al. 2017).

The misidentification of seed type could bring several implications. Farmers make numerous management decisions around their perception of the seed type selected, including what field is used or how much fertilizer is applied. To the extent that the misidentification of seed type leads to suboptimal management decisions, it may result in lower yields or lower net farm returns. In addition, incorrectly identified seed type necessarily adds considerable "noise" to the data set on agricultural outcomes that each farmer mentally builds over the course of their farming career. In this way, it could slow and distort the farmers' learning process. Finally, if a farmer intends to adopt an improved seed variety and sees poor outcomes only because the seed was misidentified, it could serve as a rationale for dis-adoption. This could hinder the agricultural growth that might be achieved with more widespread use of improved seeds.

In this paper, we examine how accurately farmers in Tanzania report on the type of maize seed they've cultivated. Farmer reports from a household survey are therefore compared with the results of crop sample deoxyribonucleic acid (DNA) analysis, which is considered to be the gold standard method for crop variety identification (Wossen et al. 2019). Crop observations are categorized as "true negative" (correctly reported as a local variety), "true positive" (correctly reported as an improved variety), "false negative" (type II error - incorrectly reported as local when the seed is determined, through DNA analysis, to be improved), or "false positive" (type I error - incorrectly reported as improved when the DNA results indicate it is a local variety) (Figure 1).

Figure 1. Seed categories

	DNA results	
Farmer report ↓	Local	Improved
Local	True negative	False negative (type II error)
Improved	False positive (type I error)	True positive

We explore the following research questions:

1. What are the rates of accurate reporting of local or improved seed types, as well as type I and type II errors (over- or under-reporting of improved seed adoption)?

2. What are the correlates of correct farmer-reporting of seed type?

3. How do rates of input use and intensity vary across the four categories of seed?

4. How do yields vary across these four categories, and are any differences plausibly explained by variations in input use?

5. Do the detected correlates of improved seed use vary, depending on whether we rely on farmer reports or DNA evidence?

6. Does the detected yield effect of improved seed vary, depending on whether we rely on farmer reports or DNA evidence?

This paper makes several contributions to the literature on improved seed use in SSA. First, it expands on the thin evidence base regarding patterns of seed type misidentification in household surveys (Floro et al. 2017; Kosmowski et al. 2018; Labarta et al. 2015; Maredia et al. 2016; Labarta et al. 2015; Wossen et al. 2019). It therefore sheds light on how generalizable are others' results (from Colombia, Bolivia, Ethiopia, Ghana, Zambia, and Nigeria) and whether patterns vary by crop. Second, by incorporating DNA analysis directly into a large-scale household survey, it offers insight beyond the smaller pilot studies that have been conducted, and further produces some practical lessons for future studies of a similar nature. Third, we extend the scope of existing studies by characterizing seed prices and input intensities across observations that are correctly or falsely identified as local or improved. This provides insight into how farmers perceive their seed and whether farmers might be misallocating inputs when they mis-categorize seed type.

The remainder of the paper is organized as follows: Section 2 details the methods available to gauge seed variety adoption, along with the rates of correct reporting found in other studies that incorporate DNA analysis. Sections 3 and 4 introduce the data and methods used in analysis. Results are provided in section 5, with robustness checks presented in section 6. A discussion follows in section 7.

2. Background on DNA Fingerprinting for Seed Varietal Identification

Several methods are available to measure seed variety adoption. At the population level, expert elicitation and seed sales inquiries are used to gauge the diffusion of seed types or varieties in a country or region (Abate et al. 2017; Walker and Alwang 2015). At the level of households or crop observations, household surveys with farmer reports are by far the most common method used to identify seed types and varieties (e.g., Alwang et al. 2018; Kassie et al. 2011; Shiferaw et al. 2014). Surveys vary in the level of detail collected, as they may ask for the seed type only, the seed variety only, or both. Household surveys may also collect information on plant descriptors, or such surveys can involve the use of visual aids to assist farmers in variety identification (Kosmowski et al. 2018; Maredia et al. 2016). Another possible (though uncommon) augmentation of household surveys includes taking photographs in farmers' fields to facilitate expert identification (Maredia et al. 2016).

The declining price of DNA fingerprinting and the application of this technology in surveys presents an opportunity to assess the accuracy of the more common methods of crop variety identification (Kosmowski et al. 2018; Rabbi et al. 2015). Several recent studies have endeavored to do so, eliciting farmer reports of crop varieties in the usual manner, while crop samples are collected from farmers' fields and analyzed in a laboratory.

Benchmarked against the results of genotyping, some studies find under-reporting of adoption of improved crop cultivars. In Zambia, Maredia et al. (2016) find that bean farmers under-report their use of improved seed, with self-reports ranging from 4-13%, while DNA results find this rate to be 16%. In Ethiopia, Tizale et al. (2015) measure rates of improved wheat adoption of 62% (based on farmer reports), as compared to 96% (based on genetic analysis). For maize, these figures are 56% and 61%. In Bolivia, Labarta et al. (2015) find the adoption rate of improved rice to be 42% with self-reports, or 45% with DNA analysis. However, approximately 12% of farmer reports are either type I or type II errors.

In Nigeria, Wossen et al. (2019) find that 54% of households report growing improved cassava, though DNA analysis indicates the true adoption rate is 69%.

Other studies find over-reporting. In Colombia, Floro et al. (2017) analyze the cultivation of improved cassava varieties and find that farmers are likely to over-report their use of improved varieties. Specifically, while DNA evidence indicates that 9% of households in their study grew improved cassava, 17% of farmers self-identified as growing an improved variety. In a study of improved sweet potato adoption in Ethiopia, Kosmowski et al. (2018) find that the rates of type I and type II errors balance out, with 20% of farmers incorrectly referring to a local variety as being improved, and 19% incorrectly reporting an improved variety as being local. With the exception of Tizale et al. (2015) and Wossen et al. (2019), all studies summarized here were conducted at a pilot scale.

3. Data

This study draws from the Varietal Monitoring for Realized Productivity and Value in Tanzania survey, implemented by the Tegemeo Institute for Agricultural Policy and Development (Tegemeo 2017), in partnership with Sokoine University of Agriculture (SUA). Household survey weights were generated with input from the Tanzania National Bureau of Statistics (NBS), although these are only used in a robustness check. Prior to the data collection, a reference library for maize varieties, including both landraces and improved varieties, was established by the Mikocheni Agricultural Research Institute (MARI) under a pilot project funded by the Alliance for a Green Revolution in Africa (AGRA). As part of the current study, genomic data were extracted by MARI and then sequenced by Diversity Arrays Technologies, based in Australia (DArT).

The crop samples for this study were collected from survey households in June-August 2016, and the survey itself was conducted from October 2016-January 2017. Because the crop samples were generally collected in the Northern zone before harvest, though were not as well-timed in other zones, this study focuses on three regions in the North: Manyara, Arusha, and Kilimanjaro (Figure 2). Furthermore, because maize is the most common crop in these regions, this study focuses only on maize.[2] In total, the zonally-representative survey includes 1,548 households in the Northern zone, of whom 1,195 grew maize in the 2015/16 main season. The survey captures detailed information on crop production over the previous year, including crop choice, application of inputs, and harvest quantities. Notably, farmers report the seed type (local, hybrid, open-pollinated variety, or a combination) for each crop in each field.[3] They further specify the seed variety for all seeds that are identified by the farmer as being improved.

All households in the Northern zone were targeted for crop sampling, and samples were taken directly from the field toward the end of the main growing season. For this reason, samples could not be taken if the harvest was already complete at the time of sampling. If a household grew maize on more than one field, the respondent identified the field most important to the household's food security (the

[2] Across Tanzania in 2014/15, maize accounted for approximately 42% of the cropped area and was produced on 3.4 million farms (NBS 2016).

[3] The survey questionnaire defined recycled seed as "one that a farmer has saved from own/previous harvest, and the original material from which the first harvest was obtained was a new seed of improved/hybrid variety." It follows that local seed was, by definition, *never* derived from a released variety. However, we are uncertain how often this definition was provided to respondents in practice.

"primary" field), and this was selected for sampling. Thus, the data are not intended to be representative of all maize grown in the study site, and survey weights are not used in our main analysis. Samples were collected from 845 households, or 68.12% of maize-growing households. There are 20 observations for which seed variety could not be identified through genotyping, and an additional four observations lack information on realized harvests. These have been dropped from the analysis, leaving a matched sample size of 821.

Crop samples were analyzed by DArT, where the genetic match for seed variety and the level of purity were identified. The DNA material was compared with a reference library of maize varieties, using single nucleotide polymorphism (SNP) molecular markers, and an observation is considered to be an improved variety if the identified primary constituent (IPC) matches that of a released variety at a purity level of at least 70%. The DNA analysis includes identification of the specific local seed variety, although in the household survey, seeds reported as being local are not specified at the variety level. The years of release of various seed varieties found in the data set were gathered from the Tanzania Official Seed Certification Institute (TOSCI 2017) and the Diffusion and Impact of Improved Varieties in Africa (DIIVA) project (ASTI 2017).

Figure 2. Study site

4. Method

As detailed earlier, maize observations from which a crop sample was taken are categorized as being either "true negative", "true positive", "false negative" (type II error), or "false positive" (type I error) by comparing farmer reports and the results of genetic analysis. Maize that is reported as improved and was recycled is considered to be improved in the main analysis, although we conduct a robustness check to explore whether results are sensitive to this decision. The four categories are then analyzed descriptively to determine how they vary in terms of seed source, seed price, input use and intensities, and realized yields.

To discern the correlates of a farmer correctly reporting a seed type as being improved or local, the following equation is used:

$$Correct\_ID_{ij} = \alpha + \boldsymbol{P}_{\boldsymbol{j}}'\boldsymbol{\delta} + \boldsymbol{H}_{\boldsymbol{i}}'\boldsymbol{\delta} + \varepsilon_{ij} \quad (1)$$

where $Correct\_ID_i$ is an indicator of whether maize observation i on field j is correctly classified by a famer, $\boldsymbol{P}_{\boldsymbol{i}}$ is a vector of field characteristics, $\boldsymbol{H}_{\boldsymbol{i}}$ is a vector of household and farm characteristics, including demographic composition, wealth, and access to agricultural extension, and ε_{ij} is a stochastic error term. Recall that each household has one sample, such that i indexes both the maize observation and the household. Summary statistics of most variables used in analysis can be found in Table A1 of the appendix.

To explore whether the detected correlates of improved seed adoption differ with different methods of identifying improved seed, we use probit models that alternately treat self-reports or DNA results as the binary dependent variable. The equation is:

$$Improved_{ij} = \alpha + \boldsymbol{P}_{\boldsymbol{j}}'\boldsymbol{\delta} + \boldsymbol{H}_{\boldsymbol{i}}'\boldsymbol{\delta} + \varepsilon_{ij} \quad (2)$$

where $Improved_{ij}$ is an indicator of whether crop observation i on field j is improved seed (1= improved, 0= local), and this status is derived alternately from farmer reports and DNA analysis. Linear regressions are then used to identify the correlates of maize yield, with the key regressor being either the self-reported improved seed status or the status determined through DNA analysis. The equation is:

$$Y_{ijr} = \alpha + \pi\left[Improved_{ijr}\right] + \boldsymbol{X}_{\boldsymbol{jr}}'\boldsymbol{\delta} + \boldsymbol{H}_{\boldsymbol{ir}}'\boldsymbol{\delta} + \gamma_r + \varepsilon_{ijr} \quad (3)$$

where Y_{ijr} is the yield (kg/ha) of crop observation i on field j in region r, $Improved_{ijr}$ is the improved seed status (1= improved, 0 = local), $\boldsymbol{X}_{\boldsymbol{jr}}$ is a vector of characteristics of field j in region r, $\boldsymbol{H}_{\boldsymbol{ir}}$ is a vector of household and farm characteristics, and γ_r is a region fixed effect.

Finally, a linear regression is again used to determine whether correct reporting of improved status is a statistically significant correlate of yield, after controlling for other inputs and field/plot characteristics. The equation is:

$$Y_{ijr} = \alpha + \boldsymbol{Cat}_{\boldsymbol{irj}}'\boldsymbol{\beta} + \boldsymbol{X}_{\boldsymbol{jr}}'\boldsymbol{\delta} + \boldsymbol{H}_{\boldsymbol{ir}}'\boldsymbol{\delta} + \gamma_r + \varepsilon_{ijr} \quad (4)$$

where Y_{ijr} is yield and $\boldsymbol{Cat}_{\boldsymbol{ijr}}$ is a vector of categories, including true positive, false negative, or false positive.

5. Results

Table **1** provides the rates at which seed type is correctly reported in the household survey. 72.72% of sampled maize observations are characterized as being improved, while results of the DNA analysis of these same maize observations reveal that 70.65% are actually improved. (Among all 1,185 primary maize fields, including those that were not sampled and are therefore excluded from this analysis, households report that 71.48% are improved. And among all 1,565 maize fields, including those that were not listed as being the primary field, households report that 72.14% are improved.)

Overall, 71.62% of observations are correctly reported by farmers as being local or improved. This leaves a considerable portion of observations that are mis-categorized as either false positives (type I errors) or false negatives (type II errors). It is somewhat more common for an observation to be falsely categorized by farmers as improved: among observations that are truly improved (according to the DNA analysis), 81.38% are correctly reported as improved, and among those that are truly local, 51.87% are correctly reported as such. At this coarse level of categorization, it seems that maize farmers are simply more likely to believe that they have sown improved seeds.

For seed that was classified by the farmer as being improved, the survey also captured details on the seed source and history. This information provides at least a partial view of why type I errors may be so common. The results of Table 2 show that it is common for seed that is sourced from other farmers to be falsely reported as improved (a type I error). At the same time, it is somewhat more common for seed that is sourced from agro-dealers or the Ministry of Agriculture (as compared seed obtained from other sources) to be correctly reported as improved. This suggests that seed type uncertainty may stem from certain ambiguities of the informal seed system, in which farmers (perhaps unintentionally) mischaracterize the seed being sold or exchanged amongst themselves. Note that 30.65% of seed observations that were characterized as improved and had been recycled were determined, through DNA analysis, to be local.

The specific seed variety was only asked in the household survey for seed that was reported as improved, and so the rate of correct varietal identification can only be estimated for those seeds which are true positive (Table 3). In this group, 24.35% of observations are correctly reported by farmers. This rate is higher for seed that was purchased this year (27.42%), as compared with seed that was not (5.77%), and this could reflect the genetic drift or contamination that occurs during seed recycling (Morris et al. 1999), or farmers' faulty memory of long-ago purchases. We wondered whether farmers might more accurately report the seed variety for those varieties that were released long ago and are therefore better known in Tanzania. However, there is no evident correlation between the year of seed variety release and the rate at which seed observations were correctly reported (***Figure 3***). The rates of correct varietal identification within the most common seed varieties in the study site are given in Table A2 in the appendix.

Table 1. Rates of local/improved maize seed identification

	% seed
Reported rate of improved seed use	72.72%
True rate of improved seed use (DNA-identified)	70.65%
Rate at which seed is correctly identified as local or improved	71.62%
True negative	14.13%
False negative (type II error)	13.15%
False positive (type I error)	15.23%
True positive	57.49%
Observations	821

Table 2. Seed sources for farmer-reported improved maize

Source of seed	Source of seed (all)	% improved from this source (DNA results)	Test[a] (P-value)
Agro-dealer	64.09%	80.94%	0.174
Local shop	16.28%	82.47%	0.385
Recycled	10.40%	69.35%	0.044
Ministry of Agriculture	6.04%	77.78%	0.829
Other farmers	2.35%	56.25%	0.040
Cooperatives	0.50%	66.67%	0.593
Community-based organization	0.34%	100.00%	0.469
Formal source (Ministry of Agriculture or agro-dealer)	70.13%	80.62%	0.244
Informal source (excludes recycled)	19.46%	79.31%	0.973
Observations	596		

[a] Two sample t-test for equality of the proportions that are correctly reported as improved across a given source and all other sources.

Table 3. Rate of correct varietal identification among seeds correctly identified as improved

	Seed variety correctly identified
All true positive	24.35%
Recycled	15.63%
Accessed through informal source	26.05%
Accessed through formal source	25.29%
T-test (Informal = formal) (P-value)	0.867
Not purchased this year	5.77%
Purchased this year	27.42%
T-test (Not purchased = purchased) (P-value)	0.000

Figure 3. Year of seed variety release and rate of correct variety identification

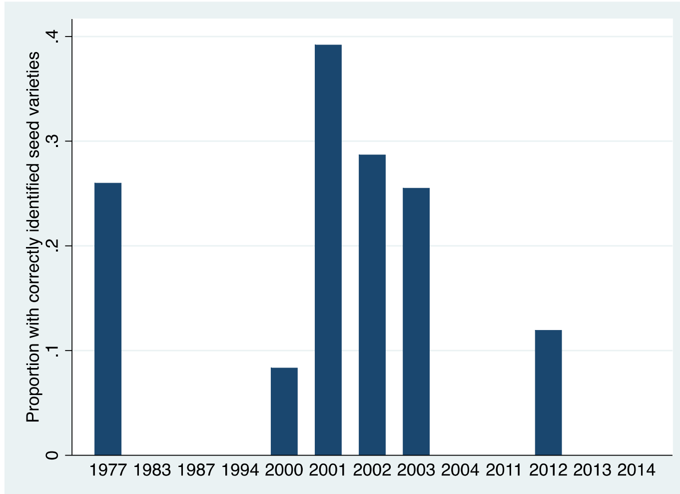

Table 4 displays characteristics of maize observations across the four categories. The columns on the right display the results of a Tukey test for the equality of mean values across different columns. A Tukey test is preferred to a t-test to account for the number of subgroups being compared, although it should be noted that it is more conservative than a standard two-sample t-test. With regard to reported seed costs per kg, it is noteworthy that costs do not differ significantly between true positive (reported as improved and DNA-identified as improved) and false positive (reported as improved but DNA-identified as local) seed. In other words, misrepresented seed is being sold for the same average price (roughly 5,400 TSh/kg) as genuinely improved seed. It follows that false positive seed is being obtained for a higher price than true negative (local) seed. In terms of seeding rate, local seed tends to be sown at a higher seeding density than improved seed (roughly 35 kg/ha, as compared with 27 kg/ha), and seed that is falsely reported as being improved is sown at the same rate as true positive seed, while false negative seed (reported as local but DNA-identified as improved) is sown at the same rate as true negative seed. This suggests that, if the optimal seeding rate varies across seed type, farmers' misperceptions of seed type may be driving them to apply inputs in a suboptimal manner.

With regard to the application of inorganic fertilizer, farmers are more likely to apply fertilizer to false positive seed than true negative seed (at 33% versus 18%). Fertilizer is also applied with greater intensity on true positive seed, as compared with false negative seed (35.87 kg/ha versus 19.30 kg/ha, on average). It therefore seems that farmers apply more fertilizer when they perceive—correctly or incorrectly—that they have sown an improved variety, and this again suggests that farmers' self-report errors steer them to differentially apply inputs in a manner they might consider to be suboptimal. Interestingly, there is a significant difference in the rate of organic manure application to true negative and false negative seed (at 11% versus 26%). This is the only evidence suggesting that farmers who falsely report improved seed as "local" may actually harbor uncertainty or suspect it is not truly local, and this is revealed in their choices around manure application.

Average yields across the four categories are presented in Table 5. As expected, the highest average yield is realized with true positive maize seed, at over two tons per ha. In addition to the benefits of improved seed, farmers often apply fertilizer and manure in greater amounts to these crops (even if the difference is often not statistically significant) (see Table 4). False positive yields were considerably lower, on average, than true positive seeds (P=0.000). This is also not surprising, though one imagines that farmers might be disappointed with these results and opt to dis-adopt improved seed (even if they had not, in actuality, been growing improved maize).

The false negative seeds are perhaps the most mysterious, resulting in the lowest average yields even though the seed type was truly improved. It is not immediately clear why this would be the case. Our results are not consistent with the pattern observed for cassava in Nigeria (Wossen et al. 2019), where the estimated yield advantage of improved varieties is larger when using DNA-referenced crop types than when using farmer reports. In Tanzania, it instead seems that the average yield gap between local and improved varieties is smaller when referring to the DNA-referenced seed types, dropping by roughly 200 kg/ha. Perhaps, holding other factors constant, the higher yields of improved seed are observed mostly when fertilizer is applied at the rate intended for improved seed (Table 4), as these are considered complementary technologies (Wainaina et al. 2016). It is also possible that false negative seeds were previously considered by farmers to be improved, though the seed vigor had been degraded so thoroughly over generations of recycling that farmers no longer perceive them as "improved". In other words, the lack of correlation across farmer-reported and DNA-identified seed type for these seeds may reflect a divergence between the farmers' definition of "improved" and what DNA fingerprinting technology is able to detect. This possibility will be discussed further in section 7.

Table 4. Maize seed identification, seed characteristics, and input use

	(1)		(2)		(3)		(4)		Tests[b]			
	True negative (TN)		False negative (FN)		False positive (FP)		True positive (TP)		TN = FN	TP = FP	TN = FP	TP = FN
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	1 = 2	4 = 3	1 = 3	4 = 2
Area under crop (ha, field size / number of crops)	0.48	0.54	0.47	0.42	0.55	0.38	0.59	0.95				
Seed cost (TSh / kg)[a]	49.38	207.67	537.01	1,184.45	4,639.86	3,000.25	4,787.29	2,388.60		***		***
Seed cost (TSh / kg) if ≠ 0	Few obs.	---	1,819.65	1,579.42	5,650.48	2,283.45	5,257.81	1,946.21	---	***	---	***
Seed rate (kg / ha under crop)	35.44	22.99	35.05	24.18	28.09	18.73	27.27	14.25		**		***
1= Use inorganic fertilizer	0.14	0.35	0.18	0.39	0.27	0.45	0.26	0.44		*		
Fertilizer rate (kg / ha)	14.56	43.57	17.90	47.46	34.11	65.94	39.13	78.55				**
Fertilizer rate (kg / ha) if ≠ 0	103.14	66.39	98.96	67.39	126.06	66.79	151.71	82.78				**
1= Use organic manure	0.11	0.32	0.28	0.45	0.21	0.41	0.30	0.46	**			
Manure rate (kg / ha)	223.67	827.83	232.07	637.81	372.82	1,026.10	622.01	1,393.28				***
Manure rate (kg / ha) if ≠ 0	Few obs.	---	828.65	989.83	1,779.82	1,599.87	2,054.73	1,864.66	---		---	***
Labor rate (days / ha)	97.02	92.21	92.71	67.72	83.71	74.01	94.32	80.17				
Observations	116		108		125		472					

[a] TSh = Tanzanian shillings

[b] Tukey test for equality of mean values. For clarity of presentation, only the most relevant cross-category comparisons are shown, and the level of statistical significance is denoted with asterisks: *** p<0.01, ** p<0.05, * p<0.1

Table 5. Maize seed identification and yields

	Yield (kg / ha)			
	Mean	SD	Tests[a]	P-values
True negative (TN)	1,596.48	1,411.66	TN = FN	0.462
False negative (FN, type II error)	1,291.86	1,197.58	TP = FP	0.000
False positive (FP, type I error)	1,618.14	1,378.26	TN = FP	1.000
True positive (TP)	2,309.14	1,704.69	TP = FN	0.000
True classification:				
Improved	1,607.71	1,391.56	Improved = local	0.000
Local	2,119.71	1,669.15		
Self-reported classification:				
Improved	1,449.61	1,318.75	Improved = local	0.000
Local	2,164.45	1,664.60		

[a] In top panel, this is a Tukey test for equality of mean values. For clarity of presentation, only the most relevant cross-category comparisons are shown. In bottom panels, this is a t-test for equality of mean values.

The correlates of correctly identifying the seed type are explored with equation (1) and presented in Table 6. Among all seed observations, being of an improved variety is a statistically significant correlate of correct farmer-reporting. Among the subsample of improved seeds, we find that being more engaged with agricultural factor markets (specifically, hiring in agricultural labor) is correlated with correctly identifying the seed as improved. In addition, farmers are more likely to correctly identify improved seed if they reside in a district with a higher proportion of maize growers that correctly identified their seed type. This variable is constructed with respect to all maize growers in the district, excluding each household in turn.[4]

We next explore whether the results of some common econometric analyses are found to shift when the improved seed status is determined through farmer reports, as compared with DNA results. First, equation (2) is used with a probit model to identify the correlates of improved seed use. The results, presented in Table 7, show that some conclusions are affected by the use of different dependent variables. Adoption of improved seed may be associated with engagement in other input or factor markets, and when using farmer reports, there is indeed a statistically significant association between hiring in agricultural labor and using improved seed. However, this relationship disappears when using DNA results. Adoption of improved seed may also be associated positively or negatively with having a source of off-farm income (Mathenge et al. 2014b). There is a positive association between having income from self-

[4] This variable (proportion maize farmers in district that correctly ID seed type) is constructed using population weights that are adjusted by the inverse probability of a primary field being sampled, to account for the fact that sampled fields differ from those that were not sampled. This process is explained further in section 6.

employment and use of improved seed, although this is only true when using farmer-reported categories. In both columns, there is a positive relationship between the rate at which other farmers in the district use improved seed and the likelihood of a farmer using improved seed.

Yield functions intended to discern the correlates of crop yield often control for seed type on the right-hand side of the equation. We now use equation (3) to explore whether the coefficient on improved seed status changes when this status is alternately sourced from respondents or genetic analysis. Results, shown in Table 8, indicate that the coefficient on improved seed is smaller when using DNA results. Thus, use of farmer-reported improved seed is associated with an increase in maize yield of 578.50 kg/ha (column 1). When self-report errors are corrected in column 2, use of improved seed is associated with an increase of 325.49 kg/ha. Recall that false negative seeds produce the lowest yields, on average (Table 5), and tend to receive inputs at levels that are indistinguishable from true negative seeds (Table 4), with the exception of the likelihood of applying organic manure. These cases are now classified as improved in column 2, and the difference between the coefficient on improved status in columns 1 and 2 is statistically significant at the 5% level (P=0.024).

In a final exercise, equation (4) is used to determine whether each category of seed (e.g., true positive, false positive) results in a statistically distinguishable yield, once other inputs are controlled for. The results in Table 9 show that the coefficient on false negative seed is negative, though usually not statistically significant, while the coefficient on false positive seed is positive but also not statistically significant. That false negative seeds have a negative coefficient, even when input intensities are included as controls, suggests that this pattern is not only reflective of diverging patterns around input applications, but rather may reflect that false negative seeds tend to be less pure or of lower-performing improved varieties than true positive seeds. The only category that produces significantly higher yields than the base group of true negative seed is true positive, and this pattern remains consistent as additional controls are added across columns 1-4.

Table 6. Correlates of correct identification of seed type (probit models)

	(1) All	(2) Improved seed (DNA results)	(3) Local seed (DNA results)
1= Field manager is a woman	-0.07**	-0.08*	-0.06
	(0.05)	(0.05)	(0.48)
Age of field manager	-0.0006	-0.002*	0.003
	(0.59)	(0.06)	(0.18)
1= Field manager completed primary school	0.02	-0.01	0.08
	(0.66)	(0.76)	(0.28)
Farm size (ha)	-0.01	-0.01	-0.03
	(0.25)	(0.29)	(0.16)
1= HH used inorganic fertilizer	0.002	0.06	-0.08
	(0.96)	(0.17)	(0.27)
1= HH hired some agricultural labor	0.04	0.11***	-0.13
	(0.19)	(0.00)	(0.10)
Proportion crop value produced that was sold	0.03	-0.05	0.32***
	(0.56)	(0.47)	(0.00)
Distance to nearest hybrid maize seed seller (km)	-0.001	-0.002	0.01
	(0.63)	(0.57)	(0.10)
1= HH accessed extension services	-0.03	-0.003	-0.14
	(0.52)	(0.95)	(0.20)
1= HH has cell phone	0.02	0.06	-0.06
	(0.69)	(0.23)	(0.47)
Proportion maize farmers in district that correctly ID seed type, excluding household *i*	0.19	0.58**	-0.67*
	(0.39)	(0.04)	(0.05)
1= Crop is of an improved variety (DNA results)	0.27***		
	(0.00)		
Observations	821	580	241

Average partial effects; P-values in parentheses; standard errors clustered at village level; *** p<0.01, ** p<0.05, * p<0.1

Table 7. Correlates of improved seed use, as identified with self-reports and DNA analysis (probit models)

	(1) 1= Improved (Farmer-reported)	(2) 1= Improved (DNA results)
1= Only a woman is the field manager	-0.02	0.02
	(0.70)	(0.74)
Age of field manager	-0.003**	-0.001
	(0.02)	(0.34)
1= Field manager completed primary school	-0.03	0.04
	(0.41)	(0.24)
Farm size (ha)	-0.01	-0.01
	(0.35)	(0.54)
1= HH used inorganic fertilizer	0.07	-0.01
	(0.12)	(0.84)
1= HH hired some agricultural labor	0.12***	0.03
	(0.00)	(0.34)
Proportion crop value produced that was sold	0.04	0.08*
	(0.33)	(0.05)
1= HH had some income from self-employment	0.06*	-0.03
	(0.09)	(0.52)
1= HH had some income from non-agricultural wage work	-0.01	-0.02
	(0.72)	(0.58)
Distance to nearest hybrid maize seed seller (km)	-0.004	0.003
	(0.28)	(0.31)
1= HH accessed extension services	0.04	-0.02
	(0.43)	(0.66)
1= HH has cell phone	0.08*	0.08*
	(0.08)	(0.07)
1= HH accessed credit	0.06	0.03
	(0.27)	(0.50)
1= HH is member of farmer group	-0.03	-0.05
	(0.60)	(0.52)
Proportion maize farmers in district using improved varieties (farmer reports), excluding household *i*	0.95***	
	(0.00)	
Proportion maize farmers in district using improved varieties (DNA results), excluding household *i*		0.52*
		(0.06)
Observations	821	821

Average partial effects; P-values in parentheses; standard errors clustered at village level; *** p<0.01, ** p<0.05, * p<0.1

Table 8. Yield functions with farmer-reported and DNA-determined improved seed status (OLS)

	Yield (kg / ha)	
	(1)	(2)
1= Improved (farmer reports)	**578.50***** **(0.00)**	
1= Improved (DNA results)		**325.49***** **(0.00)**
Area (ha under crop)	-149.70** (0.02)	-157.03** (0.02)
Seed kg / ha	24.51*** (0.00)	21.12*** (0.00)
Fertilizer kg / ha	2.80*** (0.00)	3.50*** (0.00)
Manure kg / ha	0.15*** (0.00)	0.15*** (0.00)
Labor days / ha	1.53** (0.02)	1.68*** (0.01)
1= Soil quality is good	-52.29 (0.60)	-62.10 (0.54)
1= Plot is flat	133.48 (0.26)	112.25 (0.35)
1= Field is intercropped	89.15 (0.43)	88.97 (0.43)
1= Pre-harvest crop loss	-641.92*** (0.00)	-665.62*** (0.00)
1= Female field manager	-421.22*** (0.00)	-407.14*** (0.00)
Age of field manager	-2.64 (0.46)	-3.67 (0.31)
1= Field manager completed primary school	214.08* (0.07)	210.06* (0.08)
HH members	45.82** (0.02)	51.97*** (0.01)
Distance to nearest hybrid maize seed seller (km)	-6.59 (0.38)	-10.65 (0.16)
1 = HH reached by extension services	72.11 (0.59)	101.46 (0.46)
1= HH has cell phone	232.69 (0.10)	254.84* (0.08)
1= HH accessed credit	-163.30 (0.39)	-71.09 (0.71)
1= HH is member of farmer group	-57.10 (0.82)	-53.55 (0.84)
1= Kilimanjaro region	550.61*** (0.00)	484.29*** (0.00)
1= Manyara region	1,342.46*** (0.00)	1,373.28*** (0.00)
Constant	-483.76 (0.15)	-174.05 (0.60)
Observations	821	821
R-squared	0.371	0.358
P>$\chi^2[\beta(\text{Improved} - \text{farmer report}) = \beta(\text{Improved} - \text{DNA results})]$	0.0242	

P-values in parentheses; standard errors clustered at village level; *** p<0.01, ** p<0.05, * p<0.1

Table 9. Yield functions with categories for correct identification of improved/local status (OLS)

	Yield (kg / ha)			
	(1)	(2)	(3)	(4)
Seed category (Base group = True negative)				
1 = False negative	-279.60*	-202.97	-186.18	-172.20
	(0.07)	(0.16)	(0.20)	(0.24)
1 = False positive	8.11	221.67	207.76	170.22
	(0.96)	(0.18)	(0.20)	(0.28)
1 = True positive	620.41***	695.18***	680.21***	589.50***
	(0.00)	(0.00)	(0.00)	(0.00)
Controls:				
Region fixed effects	Y	Y	Y	Y
Inputs		Y	Y	Y
Field characteristics			Y	Y
Household socio-economic characteristics				Y
Observations	821	821	821	821
R-squared	0.177	0.315	0.349	0.380

P-values in parentheses; standard errors clustered at village level;
*** p<0.01, ** p<0.05, * p<0.1

6. Robustness Checks

We have confirmed that the patterns found in section 5 are robust to different decisions made regarding the construction of variables, the delineation of the sample, and the use of weights. All results are available from the authors upon request. First, noting that instances of complete crop wipeout may skew a yield analysis, we confirmed that results are extremely consistent when the 17 observations of zero crop harvest are removed from the sample. To ensure that especially large yield values did not influence our results, we also repeated the analysis using the inverse hyperbolic sine transformation of yield. Again, our conclusions did not change with this alternative specification.

In our main analysis, when a farmer reported a seed type as being improved and recycled (saved from one's own harvest), it was classified as being improved (farmer-reported). However, it is debatable whether this ought to be regarded as improved, as the yield of recycled seed is expected to be lower than first-generation seed, rendering the status of such seed somewhat ambiguous. In a robustness check, we repeated the analysis of section 5 with a new definition of "improved (farmer-reported)", in which recycled seed is always treated as *not* improved. Results are quite consistent with this new variable construction. However, in a yield function based on equation (3), the gap between the coefficients on improved seed (using self-reports and DNA-derived classifications) increases from 253.01 kg/ha (in Table 8) to 315.30 kg/ha.

As the sampled maize fields are not representative, our intention in this study is not to make claims regarding the population of maize farms in the study site. However, we have also repeated the analysis of section 5 using inverse probability weights (IPWs), adjusting the population weights to account for the likelihood of a primary field being sampled (Table A3 in the appendix) (Wooldridge 2002). This is roughly intended to represent the population of primary maize fields. The results of this parallel analysis are very similar to section 5. However, we now see statistically significant differences between true positive and false negative seed in terms of application rates of both organic manure and inorganic fertilizer. This reinforces our impression that farm management decisions are influenced by perceptions of seed type.

7. Conclusions and Policy Implications

In this paper, we draw from an agricultural household survey in Tanzania and use DNA fingerprinting as a benchmark against which the accuracy of farmer reports of maize varietal identification is evaluated. We quantify the rate of type I and type II errors in the identification of improved seed type and consider some potential explanations in the form of informal seed sources, as well as potential consequences in the form of input allocations made under faulty assumptions of seed type. We also consider how standard approaches to analyzing household survey data may produce results that differ, depending on how local/improved seed status is captured.

We find that a majority (71.62%) of maize observations are correctly identified as local or improved, while 18.62% of improved seeds, and 48.13% of local seeds, are misidentified. These results suggest that farmers in Tanzania are slightly over-inclined to report their maize seed as being improved. This pattern is in contrast to the under-reporting observed among wheat and maize farmers in Ethiopia (Tizale et al. 2015) and rice farmers in Bolivia (Labarta et al. 2015). Seeds that are falsely reported as improved are more likely to have been obtained from other farmers, and somewhat (though not significantly) more likely to have been recycled. This may relate to the ambiguities of genetic drift when seed is recycled or cross-pollinated (Morris et al. 1999; Westengen et al. 2014) or the uncertainties inherent in sourcing seed through informal channels. Along these lines, seed obtained through a recent purchase are also more likely to be correctly identified at the seed variety level. The challenge for poor farmers is balancing a need for quality assurance with their budget constraints.

With regard to patterns of crop management, we find that management of improved seed that is perceived as improved (correctly) or local (incorrectly) does vary. For example, compared with correctly reported improved seed, the seeding rate is higher (on average) and the fertilizer rate is lower on improved seed that is incorrectly reported as local. At the same time, we find little evidence that farmers differentiate their management decisions among seed that is either correctly or incorrectly reported as improved, and the same is generally true for seed that is either correctly or incorrectly reported as local. This suggests that farmer (mis)perceptions do guide input decisions, and errors in farmers' awareness of their seed type may translate into suboptimal management practices.

We find some evidence that results differ when relying on farmer reports versus DNA analysis to categorize seed as being improved. In particular, the measured yield benefit of improved seed use is smaller in magnitude (by 202.84 kg/ha) with a DNA-derived categorization. This difference persists in econometric analysis, where application rates of inputs and field characteristics are included as controls. This suggests that the true impact of improved germplasm research is somewhat lower than would be estimated with more conventional (survey-based) methods. However, this does not tell us what the effect of crop research *would be* if farmers were more aware of their seed type. In fact, the yield benefit is greatest for true positive seed (Table 9), which suggests that agricultural research centers might maximize the return on their investments by increasing farmers' knowledge of seed type or improving quality control within the seed system.

As the costs of genotyping continue to decline (Kosmowski et al. 2018) and the application of DNA analysis to household surveys becomes more prevalent, it is worth highlighting several lessons learned from our experience. On a logistical note, it is important for crop samplers to visit households long enough before the harvest that the sample may be considered representative of a given population. It may also be advisable to provide survey respondents with a clearer explanation regarding the difference between recycled seed and seed that ought to be categorized as local (according to the survey designers). Thus, improved seed that has been recycled a certain number of times may be understandably categorized as either improved or local. In such cases, farmer reports and the results of genetic analysis might be harmonized if farmers had been provided with clearer criteria for seed classification.

For those interested in more comprehensively exploring patterns of improved seed adoption, it would be ideal to collect information on seed variety (i.e., local names), source, and history among seed that was reported as local; to collect more details on seed transactions, particularly with other farmers; and to track patterns of improved seed adoption and dis-adoption over time. Furthermore, to better understand the backstory behind any discrepancies between farmer reports and DNA evidence, it would have been fascinating to discuss the laboratory results with farmers. One imagines that these conversations could shed light on what led farmers to the responses they had provided (e.g., uncertainty versus a confident misperception), and could inform survey design to more accurately capture seed variety in future studies.

Appendix

Table A1. Summary statistics of key variables

	Mean	SD
Area (ha under crop)	0.60	0.79
Seed kg / ha	29.47	16.97
Fertilizer kg / ha	31.87	67.97
Manure kg / ha	547.18	1,294.80
Labor days / ha	92.52	83.16
1= Soil quality is good	0.69	0.46
1= Plot is flat	0.81	0.39
1= Field is intercropped	0.72	0.45
1= Pre-harvest crop loss	0.31	0.46
1= Field manager is a woman	0.18	0.38
Age of field manager	51.41	15.21
1= Field manager completed primary school	0.72	0.45
HH size (members)	5.67	2.58
Distance to nearest hybrid maize seed seller (km)	5.64	6.35
1= HH accessed extension services	0.14	0.35
1= HH has cell phone	0.86	0.35
1= HH accessed credit	0.06	0.25
1= HH is member of farmer group	0.03	0.18
Region:		
1= Arusha	0.20	0.40
1= Kilamanjaro	0.37	0.48
1= Manyara	0.44	0.50
Obs.	821	0.39

Table A2. Seed variety and rate of correct variety identification

Seed variety	Observations	Seed variety correctly identified
DK 8031	48	33.33%
DKC 8053	45	26.67%
DKC 90-89	41	14.63%
H.614D KITALE	41	31.71%
H625 KITALE	10	10.00%
KITALE H628	16	43.75%
PANNAR 4M-19	12	0.00%
PANNAR 691	38	63.16%
PHB 3253	18	0.00%
SC 403	26	23.08%
SC 513	39	46.15%
SC 627	80	51.25%
SITUKA M-1	12	8.33%

Table A3. Likelihood of maize field being sampled (probit model)

	1= Sampled
Area (ha under crop)	0.29***
	(0.01)
1= Improved seed variety (farmer report)	0.12
	(0.29)
Seed kg / ha	0.00
	(0.19)
Fertilizer kg / ha	0.00
	(0.86)
Manure kg / ha	-0.00
	(0.95)
Labor days / ha	-0.00
	(0.47)
1= Soil quality is good	-0.12
	(0.29)
1= Plot is flat	0.10
	(0.40)
1= Field is intercropped	0.06
	(0.70)
1= Pre-harvest crop loss	0.04
	(0.71)
1= Field manager is a woman	-0.25***
	(0.00)
Age of field manager	0.00
	(0.23)
1= Field manager completed primary school	0.16
	(0.20)
HH size	-0.00
	(0.92)
Distance to nearest hybrid maize seed seller (km)	0.01
	(0.65)
1= HH accessed extension services	-0.03
	(0.82)
1= HH has cell phone	0.03
	(0.81)
1= HH accessed credit	-0.19
	(0.28)
1= HH is member of farmer group	-0.13
	(0.67)
1= Kilamanjaro	0.83***
	(0.00)
1= Manyara	1.03***
	(0.00)
Constant	-0.72*
	(0.07)
χ^2	87.72
$P>\chi^2$	0.000
Observations	1,185

Coefficients; P-values in parentheses; standard errors clustered at village level; *** p<0.01, ** p<0.05, * p<0.1

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