Subsidies and Product Assurance: Evidence from Agricultural Technologies[1]

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Abstract

Markets for credence goods – goods for which quality is difficult to observe both ex-ante and ex-post – are plagued with information asymmetries whereby low-quality products are sold alongside high-quality products at similar prices. Firms cannot signal the quality of their products, and consumer demand is low. Widely used subsidies for agricultural technologies have often failed to improve adoption and profitability because many agricultural technologies are credence goods. We study the effects of a product assurance scheme in Uganda that introduced branded package labels for hybrid maize seed, a credence good. Using a market-level randomized control trial, we identify the effects of a large subsidy provided to farmers exposed to the product assurance scheme on hybrid maize seed demand, price, and quality. Adoption of hybrid maize increases by 44 percent due to the subsidy, with increased demand for both labeled *and* unlabeled hybrid maize. Prices and quality of labeled and unlabeled hybrid maize also increase in treated markets. Additionally, both quality and prices are higher for labeled goods than unlabeled goods, indicating the emergence of a separating equilibrium that allowed high-quality firms to distinguish their products. We find evidence of market changes on the extensive margin rather than the intensive margin, with fewer hybrid maize varieties available in subsidy markets and poorer-quality products exiting the market. The results suggest that, when combined with a quality signal delivered through a low-cost product assurance scheme, a temporary subsidy increases technology adoption and improves average product quality for credence goods.

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1 Introduction

Credence goods present challenges in assessing their quality both before and after purchase (Darby and Karni 1973),[1] leading to significant information asymmetries between buyers and sellers resulting in decreased demand and reduced willingness to pay for high-quality goods. The struggle to signal product quality creates opportunities for counterfeit and low-quality products to dominate the market, forming a "market for lemons" with a "pooling equilibrium" where high- and low-quality products are priced the same (Akerlof, 1971). These credence goods encompass vital items like medicines and productivity-enhancing agricultural inputs. Recent evidence from low-income countries reveals the prevalence of substandard agricultural inputs such as hybrid maize and herbicides, leading to low demand from households despite the potential benefits these inputs offer (Bold et al., 2017; Tjenstrom et al., 2017; Fairbairn et al., 2017; Kilic et al., 2017).[2] In such countries, where a significant portion of the population engages in farming, the adoption of these productivity-enhancing inputs remains low (Aker, 2011; Kelly et al., 2003; Duflo et al., 2011; Morris et al., 2007), partly because information asymmetries hinder farmers in assessing returns to inputs. Effectively mitigating information asymmetries becomes crucial so that households can make informed choices, firms can differentiate their high-quality products, and overall market dynamics can shift towards favorable outcomes for all stakeholders involved.[3]

Addressing information asymmetries in credence goods markets can be achieved partly through certification schemes since certifiers are able to aggregate information from infrequent purchases (Dandrove and Jin, 2010), and consumer behaviour should be able to discipline sellers to produce higher quality. Certification schemes can effectively turn credence goods into experience goods (McClusky, 2000). However, they are costly, require strong enforcement, and are prone to corruption (Auriol and Schilizzi, 2015). Another

[1] Nelson (1970) and Darbi and Karni (1973) categorize products into search (consumers can assess quality prior to purchase), experience (consumers can only assess quality after purchase and by trying it), and credence goods (consumers cannot assess quality before or after purchase – after purchase, there may be various reasons that a product appears to have been low quality).

[2] If consumers cannot tell high-quality from low-quality products, then they assume an (weighted) average quality in the market based on their knowledge of the probabilities of each type, leading to a pooling equilibrium in prices.

[3] If producers can credibly signal quality to buyers, a separating equilibrium results where product quality is known, and equilibrium prices are differentiated accordingly. This equilibrium is more efficient than the pooling equilibrium (Saitone and Sexton, 2010).

approach is subsidies, allowing consumers to accumulate their own information through experience at lower costs and learn about quality (Carter et al., 2014). However, credence goods complicate the learning process because their quality is difficult to assess, even after purchase, and tend to be purchased infrequently, causing learning to take longer compared to other goods (Hoel et al., 2021). Consequently, temporary subsidies may provide limited additional quality signals, possibly explaining the underwhelming performance of agricultural input subsidies (Jayne et al., 2018). As noted by Ashraf et al (2013), information and subsidies are complementary because information provision can change consumers' elasticity of demand and thus the impact of subsidies.

In this paper, we evaluate the impact of a novel intervention combining a product assurance scheme for agricultural inputs introduced by the government of Uganda, called Kakasa, and an experimental input subsidy for hybrid maize seed purchased through the scheme. The product assurance scheme uses detailed package labels to provide a signal of product authenticity, and we experimentally provide information about these labeled products in 1 of 2 paired communities in each of 120 markets. We also experimentally introduce subsidies in 60 of 120 randomly selected markets that serve the 240 communities. The subsidy encourages farmers to try the labeled maize, thereby creating a demand shock. We estimate effects on demand, price, and quality for hybrid maize in agricultural markets.

The labeling scheme involved adding a scratch-off label to the packaging that provided an authentication code used to confirm that the labeled product is what is claimed on the packaging (brand, package size) via SMS. Upon seeing a costly signal, buyers infer that the seller's discounted sum of future profits must be large enough to justify the initial fixed cost of joining the scheme; otherwise, firms would not have made the investment (Klein and Leffler, 1981; Dewally and Ederington, 2006), leading to increased demand for hybrid maize among farmers. Consequently, prices for product-assured hybrid maize are expected to rise, potentially improving the overall quality of the inputs and creating a separating equilibrium whereby prices for higher-quality products are higher than products of lower quality. The subsidy was for the entire cost of a 1kg bag of hybrid maize seed that was given out at community meetings that also informed farmers that the product was available and could subsequently be redeemed after demonstrating proof of purchase.

We begin by noting that the seed producers who opted into the labeled scheme were those that produced higher-quality products at baseline. This was expected since there was a cost to joining the scheme and as theory suggests, only firms that would benefit from

signaling their quality would join (Jovanovic, 1982). Next, we document three main results. The subsidy led to a 55 percent increase in the purchase of hybrid maize seeds, indicating a large increase in demand. Purchases of labeled maize seeds were substantially higher in the treatment markets, but farmers in treated markets also purchased unlabeled hybrid maize seeds. This result suggests that subsidies can indeed encourage adoption of credence goods when combined with a signal of product quality. Second, the price and quality – the germination rate – of labeled hybrid maize were higher than unlabeled products at endline (across all markets), suggesting the emergence of a separating equilibrium. This result suggests that firms producing high quality products attempted to use the labeled scheme to capture information rents through higher prices for seeds that signaled higher quality by joining the scheme. Third, prices *and* quality of both labeled and unlabeled hybrid maize seed increased in markets in which farmers received subsidies, indicating that there were spillovers from labeled products to unlabeled products, thereby improving the average quality of all products on the market.

We consider two channels for these results. First, the intervention could have led to change on the extensive-margin in the composition of varieties available in markets. Poor-quality products (labeled or unlabeled) may exit the treated markets, leaving only higher-quality products. Alternatively, shops selling poorer quality products could exit the market or shops selling lower quality products may exit markets. Second, there could be changes on the intensive margin whereby companies change their internal processes (such as production methods) or shops change their practices (for example, better storage) that improve quality.

We find modest evidence that there were changes on the extensive margin with fewer varieties available in treated markets. Since the overall quality of products in treated markets improved, this suggests that low-quality products exited the market. Additionally, we find no evidence of differential market composition in shops – there are no differences in the number of firms open, enter, or exit the market between treated and control markets. We do not observe changes in the characteristics of the products available in markets, however (storage practices, source of procurement, package size, etc.) suggesting that this intensive margin of potential quality improvements is absent. Companies did not change what their products looked like in treated markets and there is no evidence that shop owners did either. Consequently, we hypothesize that the improvement in the market equilibrium was at least partly because the varieties that joined the labeling scheme were of higher quality in the first

place; precisely what theory predicts. The product assurance scheme enabled companies to use price as a signal of quality and resulted in a separating equilibrium.

Finally, we note that companies did not label all of their products; 25% of companies labeled some but not others. For example, 1kg bags of maize could be labeled while the same variety in a 0.5kg bag may not be and they are often available beside one another in a shop. Product assurance schemes thus may be preferred to quality assurance or minimum quality standards schemes since product quality does not actually need to be tested so they are much cheaper for regulators to implement. The main takeaway is that subsidies for credence goods may not be enough to encourage adoption; credence goods may require an additional signal of quality to overcome the effects of information asymmetries.

We bring together two long-standing strands of literature. First, we contribute new evidence within the certification and experience/credence goods literature. Many studies target interventions to farmers rather than shocking markets.[4] measure adoption only, and only one study apart from ours measures market-level outcomes. The study most related to ours is that of Hsu and Wambugu (2023), which examines the impacts of a similar product assurance scheme for maize in Kenya. They randomly inform farmers about how to identify quality maize packaging, including the presence of a scratch-off label, and in a separate treatment arm, encourage farmers to report fake seeds. They find no impact on prices or quality, but a shift in where farmers purchase their products and they find that some shops exited the market. The labels they study are minimum quality standards rather than product assurance, which tends to be much more expensive for regulators. Gharib et al (2021) also study e-verified maize in Kenya and measure farmers' WTP for the certified seed and for seed from different sources (local shops versus seed companies). They find that training about package innovations is important for WTP and thus take-up. Mastenbroek et al (2020) study certified open pollinated varieties in Northern Uganda and inform farmers about the products' attributes.[5] They also elicit farmers' willingness to pay (WTP) for the certified seeds and find that the information did not affect WTP. They conclude that there must be another barrier to adoption. Kariuki and Hoffman (2022) study the provision of information and on-

[4] Recent studies (cite, Emilia is one) have measured the impact of One Acre Fund, which introduces new retailers that only sell high quality agricultural products. They are not certified but induce an additional player into each randomly selected market. Bjorkman-Nyqvist, Svenson, and Yanagizawa-Drott (2022) implement a similar intervention for anti-malarials in Uganda.

[5] We focus here on low-income countries because of the extremely low regulatory capacity. In high-income countries ….. cite some literature.

site testing of maize flour brands that are certified by a third party and less likely to be contaminated with aflatoxin (a carcinogenic fungal byproduct, which is an unobservable attribute). Testing on-site contributed to persistent take up of safe maize flour, suggesting that more specific information is helpful.[6] These studies suggest that, for credence goods, information may not be enough.

Second, we contribute to the literature on subsidies for agricultural inputs, which have had mixed results (Jayne, 2018). Temporary subsidies tend to have short-lived effects on adoption. Lybbert et al (2023) find that a subsidy for pulses in India initially led to a 5—200% increase in pulse farming, but by the third year, when the subsidies phased out, pulse farming returned to previous levels. Xine et al (2022) study a fertilizer subsidy in Tanzania and find that impacts on productivity and welfare are limited. In contrast, Carter, Lajaaj, and Yang (2021) find that a subsidy for improved maize seeds in Mozambique increased adoption during the provision of the subsidy, but also that the effect persisted after the subsidy was removed. Carter et al (2013) find that demand for vouchers for hybrid maize and fertilizer in Mozambique was relatively low – only 28% of farmers took up the subsidy. The subsidy did lead to increased adoption, however, and in a follow up paper Carter et al (2014) finds that take up of fertilizer persists in seasons after the subsidy expires; the subsidy may have led to learning about optimal fertilizer use. Take up of maize does not persist. Duflo, Kremer, and Robinson (2011) also find that a small discount on fertilizer can encourage farmers to adopt fertilizer at first. However, even a large discount does not result in persistent adoption of fertilizer. This pattern indicates that subsidies for maize (a credence good) tend to be less successful and persistent compared to subsidies for fertilizer (an experience good), when it comes to promoting adoption. Once again, this highlights the presence of a missing market for credence goods.

We combine information about a certification scheme that reduces information asymmetries between buyers and sellers with subsidies that allow farmers to try the new product to learn for themselves. Our findings are consistent with those of Ashraf, Jack, and Kamenica (2013). While we cannot show complementary effects of the two interventions since it was not a factorial design, we conjecture that subsidies for credence goods may need a quality signal to be effective. Additionally, product assurance schemes, while less rigorous because they do not involve testing quality, can still be effective. Two features of these

[6] Norton, Hoel, and Michelson (2020) find similar evidence for fertilizer in Tanzania.

schemes can induce spillovers that generate positive market equilibria. First, the absence of quality testing makes them cheaper, enabling certifiers to reduce costs and possibly serve a larger market. Low-quality firms still will not select in if the price is too high. Second, product assurance does not set a minimum standard, so companies can choose to label some of their products and not others, generating spillover effects into close substitutes. Our demand shock driven by a subsidy in addition to the provision of information and certification may explain why we see an increase in adoption, price, and quality.[7]

The rest of the paper proceeds as follows: section 2 describes the context and the intervention. Section 3 provides details on the experimental design of the study and estimation of treatment effects. Section 4 presents the results, and section 5 concludes.

2 Context and Intervention

2.1 Context

Maize in Uganda. At the start of the study, maize was the second most highly produced food crop in Uganda as well as the fifth most exported crop (Uganda Bureau of Statistics, 2014). Most maize is grown by smallholder farmers. The Government of Uganda has promoted high-quality hybrid maize seed varieties, the use of fertilizers, and minimum or zero-tillage using herbicides in line with the country's Plan for Modernisation of Agriculture (National Agricultural Research Organization (NARO), 2010). However, use of these agricultural inputs is low, in part due to fear of counterfeiting Bold et al. (2017). There are two maize growing seasons in Uganda. First season runs between March and June and second season runs between July and September. The first season is the primary growing season when almost all farmers (90 percent) grow maize (compared with 82 percent of farmers in the second season).

Hybrid maize seeds. Hybrid maize seeds offer several advantages: they are bred to withstand climate shocks and pests, and, when used appropriately, tend to result in higher

[7] Bai (2021) studies the addition of a high-quality label for watermelons (an experience good) in China and finds that labeled products are of higher quality but it is difficult for sellers to sustain the labeling scheme.

yields. Hybrid maize is a credence good because it is difficult to assess quality ex-ante (a farmer cannot assess the quality of the seed by looking at the bag) and ex-post (output depends on factors such as weather, soil conditions, correct application of the product, etc.) (Hoel et al. 2021; Auriol and Schilizzi, 2015). Farmers sometimes do not know if they are using hybrid maize or not, and even when they do, they often do not know the precise variety (Kibrom's paper).

Seed quality. Fake seeds have garnered a lot of attention in Uganda, both in the literature (Bold et al, 2015; Barriga and Fiala, 2018) and in the media (Joughin, 2014; Mastenbroek et al 2020). The concern is the replacement of, or mixing hybrid maize seeds with counterfeits. These fake seeds often appear similar (same packaging, dye of the grains, price). In this case, the maize in the bag will not genetically match what it should be and will not perform accordingly. However, maize quality can be influenced by several factors in addition to maize genetics. Poor storage practices lead to pest infestations, high levels of moisture, sub-optimal oxygen levels, and incorrect storage temperatures. Indeed, Barriga and Fiala (2018) find that 98% of maize samples collected along the supply chain for seed in Uganda is genetically pure; it is the storage practices that are the main factor in low-quality seeds that do not germinate. They find that quality (measured by moisture content, germination, vigour, and genetic markets) is highest when seed is purchased through breeders but deteriorates as sample move down the supply chain to distributors and then retail shops.

Maize markets in Uganda. The market for hybrid maize in this context has several important features. First, it is characterized by a few large seed companies (some local and some international) that capture most of the market share alongside smaller seed varieties that are predominantly produced locally. Note also that some seed companies produce more than one seed variety.

Second, prices of hybrid maize tend not to be associated with high quality, indicating a pooling equilibrium. In Table 1, we present a regression of the price per kg of hybrid maize seeds at baseline in the markets in this study on prices, and even our most parsimonious specification in column 1 with no controls shows an insignificant coefficient. Consequently, before the interventions, we observe a pooling equilibrium in these markets.

Table 1: Quality and Prices at Baseline at Sample level

	(1)	(2)	(3)	(4)	(5)
	Maize unit price (UGX per kg)				
Quality (Roger's distance)	1036.55	2103.03	2121.53	2158.15	486.73
	(1217.75)	(1361.33)	(1357.59)	(1351.29)	(1446.29)
Number of hybrid maize seed bags believed fake (of 10)			-90.88		
			(155.66)		
Used hybrid maize				-1632.93	
				(1515.39)	
Observations	215	215	215	215	215
R^2	0.617	0.678	0.678	0.680	0.557
Including controls	No	Yes	Yes	Yes	Lasso
Including ML quality beliefs	No	No	Yes	No	Yes
Including ML average adoption	No	No	No	Yes	Yes

Notes: Standard errors in parentheses. Most maize samples have 20 maize seeds. Standard errors are clustered at the ML level. All regressions include market hub fixed effects. Control variables include dummies of sample collection week, container type, sample size, location where the sample is stored, ML average proportion of shops carrying maize, ML average proportion of shops having maize container size at 2kg, ML average proportion of shops having maize container size at 5kg, ML average proportion of shops from distributors, wholesaler and from another district (from shop data). Missing observations in the Roger distance variable and control variables are replaced with market location and market hub averages. Regressions include a missing dummy for such variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Markets are relatively small: they have between 1 and 7 shops, on average 3. Markets for hybrid maize are also extremely thin; only ten percent of farmers used hybrid maize seed at baseline and 46 percent of them source their hybrid maize from outside their nearest market. All 120 markets in our sample had shops that sold agricultural inputs in all three rounds of data collection per the design of the overall study.[8] However, shops were included in the sample if they sold either hybrid maize, glyphosate herbicide, or inorganic fertilizer and only 40 of the 120 markets had stocked no hybrid maize seed in the past two growing seasons at baseline, and 31 at endline. While the median number of shops selling agricultural inputs in a market is 2.5, the median number of shops selling *hybrid maize* is only 1.5 – many only sell herbicide, fertilizer, and/or insecticide. Hybrid maize samples were collected in 65 markets at baseline and 63 markets at endline, with 39 markets not having any hybrid maize available for purchase at baseline or endline (and 47 markets with samples collected in both

[8] The full study also included inorganic fertilizer and glyphosate herbicide.

rounds). Consequently, our sample is restricted to the 63 markets from which we collected samples at endline.

Masumoto, Yamano & Serunkuuma (2010), find similar patterns in Uganda. The average quantity of hybrid seed purchased by the control households in their sample was 1.1 kg. The farmers in their sample also have low price elasticity of demand. [[have another look at summary statistics in other papers]]

2.2 The product assurance scheme

The product assurance scheme 'Kakasa' was implemented by the Uganda National Bureau of Standards (UNBS). The scheme was directed mainly at two agricultural inputs: glyphosate herbicide and hybrid maize seeds. The label system worked as follows:

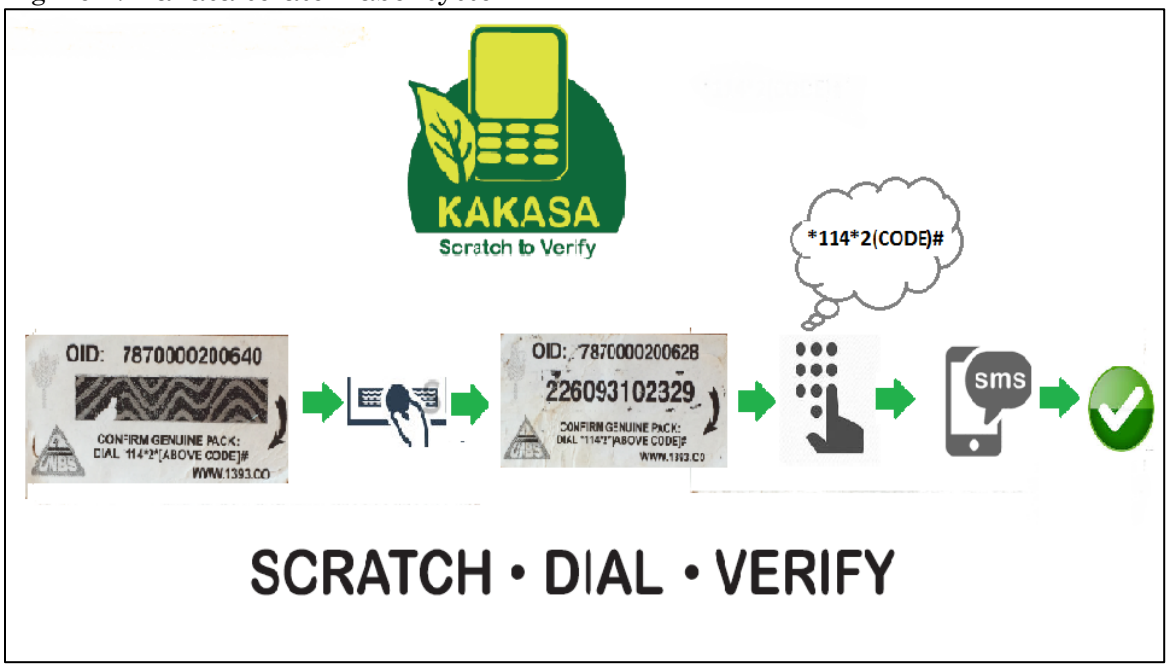
1. Labels were applied to bags of maize or bottles of herbicide by the company selling the product.
2. When farmers purchased a labeled product, they could authenticate the product by scratching the scratch panel on the label and texting the revealed code to a phone number.
3. The farmer would then receive a reply SMS with details of the product (brand, package/bottle size, and expiration date).

This would allow farmers to compare the information from the text message to the product in front of them. Note that the labeled products were not certified for quality - testing was not conducted to verify quality before the labels were provided to herbicide or seed companies.[9]

Figure 1 shows the process graphically. The government advertising campaign was extensive. It included road shows, brochures and ads in stores selling agricultural inputs, radio advertisements and segments, and even television segments. It was discussed on popular shows shown in public transportation and reached farmers quite broadly. There was also a call centre for people to report inputs for which the information did not match between the product and the SMS. The scheme was open to any seed company who wanted to apply labels to their products. Companies had to pay both a fixed costs to join the scheme and a small cost per label.

[9] Although, this practice was implemented later.

Figure 1. Kakasa scratch label system



3 Impact Evaluation Design

3.1 Intervention and randomization

The intervention had two components, both meant to induce a demand shock by alleviating information constraints. The first one focused on information to reduce short-term information asymmetries and the other focused on providing farmers a chance to test the labeled products (via a subsidy) and thus update information. In the first component, farmers received interactive voice messages whereby they were told that the labeled products existed, and how they worked. Farmers could interact with the system by selecting what further information they wanted, for example, which maize varieties had the label. Additionally, enumerators visited villages and held community meetings during which they told farmers about the labeled products, demonstrated how to use them, and held a raffle for attendees to win phone credit. These meetings were conducted twice, during the second growing season of 2016 and the first growing season of 2017. The meetings were conducted by trained enumerators on the project.

In the second intervention farmers were provided with a full subsidy to purchase a 1kg bag of labeled hybrid maize seed. These were provided in the first growing season (the

main growing season) of 2017 and were distributed at the second community meetings. Meeting participants were told that each person attending the meeting would receive a voucher for purchasing 1kg of labeled maize that day. The voucher covered most of the cost of 1 kg of hybrid maize (the average price being just over 8,000 UGX (XXXX USD), the value of the voucher). The vouchers were specially printed to avoid counterfeiting of the vouchers.[10] Community members were informed that the enumerators would re-visit the community approximately three weeks later to provide redemptions for the vouchers.[11] To redeem a voucher, the individual needed to provide the original voucher and proof of purchase of the product (this could be a receipt, an empty container, or a full container of the labeled product if they had not used it yet). If the label on a product was not scratched to authenticate it, the enumerator would do so with the farmer upon redemption of the voucher. Enumerators kept track of how many vouchers were given out in each community and how many were redeemed. Before they returned to the community, the community leader was informed of the day that they would be returning so that they could inform community members of the date and encourage them to attend.[12]

With each of 120 markets in our sample and two communities per market, there were a total of 240 communities. One of the paired communities in each market was randomly assigned to receive the information interventions – the community meetings and interactive voice messages. Of those 120 communities treated with information, half (60) were selected to also receive the discounts. This market-level randomization was not stratified. Consequently, the design is as follows:

[10] They were printed on a special type of paper whereby rubbing the back of the paper causes faint words printed on the back to disappear for a few moments and then re-appear. This type of paper was only available in the US and not in Uganda, so we are confident that the vouchers were not counterfeited. Vouchers could be split into two parts (on a perforated line). Community members kept the top part, and the enumerators kept the bottom part. On the bottom, the names of the voucher recipients and the community IDs were recorded to keep track of the vouchers given out. Both parts had a unique code identifying the voucher number.

[11] We collected detailed data on contact information, particularly for the 10 households in each community that were part of our intensive surveying. Those farmers were contacted directly and asked to participate.

[12] We note that this intervention was coupled with a second intervention in which the same community receiving the subsidies was also provided with an initial community meeting in which labeled products were explained (but no subsidy was provided) and those community members also received interactive voice calls that informed them about the availability of labeled products and which varieties would have the labeled label. Additionally, a second community served by the same market was included in the sample that did not receive any programming. However, while in this paper, the identification of market-level effects is identified only off the voucher the results should be interpreted as half the communities in each market also having received these interventions in addition to the subsidy.

Table 2: Treatment arm design across 240 communities

	Information	No information
No subsidy	30 markets 60 communities	30 markets 60 communities
Subsidy	30 markets 60 communities	30 markets 60 communities

Companies

120 markets

Subsidy No subsidy

240 communities

Information No information Information No information

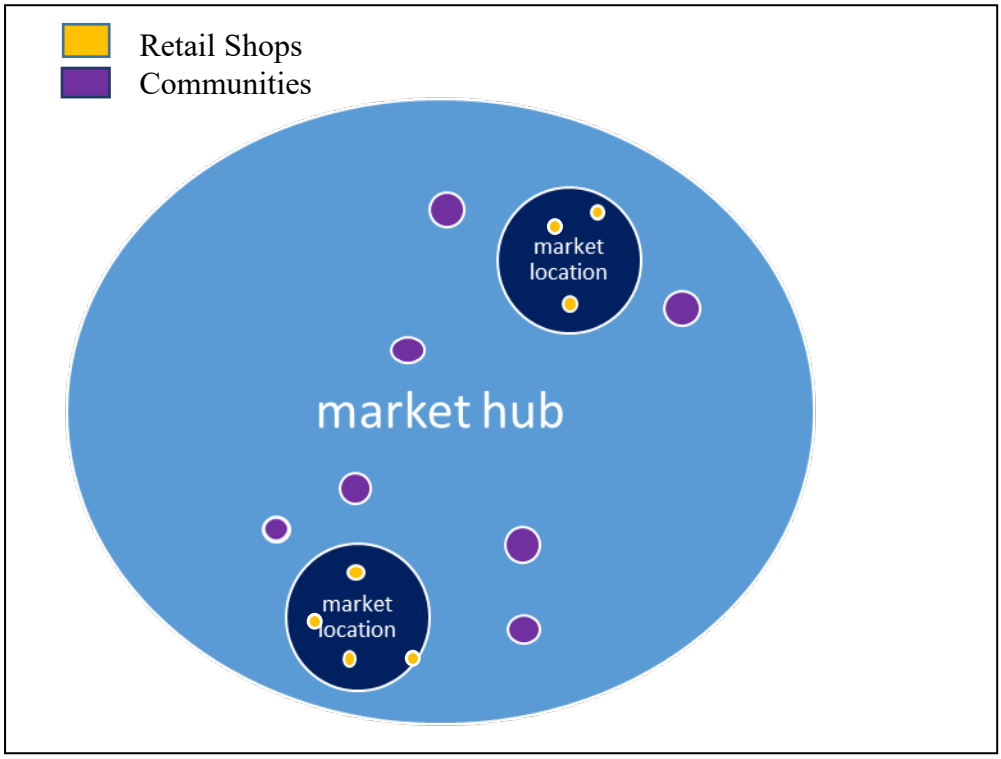
Theoretically, if disclosure affects demand, the returns to quality should increase as high-quality firms increase sales, boost prices, or both. This, in turn, should prompt sellers to raise quality. There is empirical evidence from a variety of markets including healthcare that disclosure motivates sellers to improve quality (citations). However, there is also considerable evidence from healthcare and education that sellers have attempted to game the system at the expense of consumers, specially if the measured quality does not cover all dimensions of quality or does not adjust for characteristics of consumers that can affect the rankings (citations). Consequently, this is an empirical question.

3.2 Sampling

The first step of the sampling process was identifying broad areas in which to work. We identified "market hubs" where labeled products were likely to be made available. A market hub is a major market area consisting of a collection of "market locations" covering one or more districts, centered around a major town (generally, the district town center). A market location is a collection of retail shops (often referred to as a trading center) selling agricultural inputs in the same vicinity. Each market location serves several surrounding communities (see Figure 2). The most common method for households from these communities to access

agricultural inputs is from retail shops in their nearby market location, although they may also travel to the market hub town to source their inputs. Less common was sourcing inputs directly from a distributor or traveling greater distances, to other market hubs or to Kampala, to purchase agricultural inputs.

Figure 2: Market hubs, market locations, and communities



At the start of the project, a market survey was conducted to gather lists of the market locations in these market hubs, of communities served by each market location, and of retail shops in each market location from key informants. Using the data gathered, 120 market locations (of 139 identified) were selected via stratified random sampling for inclusion in the study. Shops were then visited for a detailed survey.

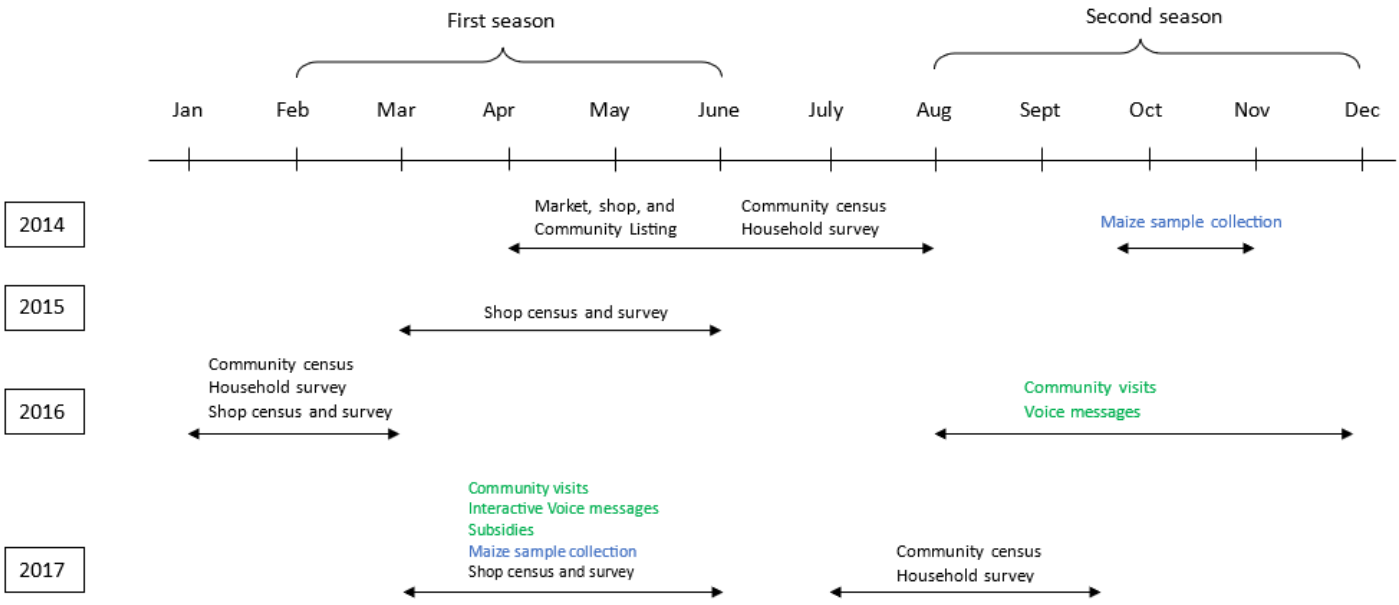
Two communities served by the same market were included in the sample for data collection and a community listing exercise (CLE) was conducted, whereby enumerators attempted to visit all households residing in the community with an average of approximately 100 households interviewed in each. From the community listing exercise, ten households were randomly selected to receive an extensive household survey. Seven households who reported in the CLE that they owned a mobile phone were selected for inclusion into the

household sample, and three households who reported in the CLE that they did not own a mobile phone were also selected for inclusion into the household sample. These households were sampled using simple random sampling.

3.3 Data

The baseline survey was conducted in July-August 2014, the midline survey in January-March 2016, and the endline in July-August 2017. The endline was conducted two 'growing seasons' after the intervention began. Each round of data collection included the CLE survey, a household survey, and a shop survey for all shops in each market. See figure 3.

Figure 3. Timeline



Notes: Blue text denotes the collection of hybrid maize seed samples for laboratory testing, and green denotes the interventions.

CLE. The CLE collected basic information about household members, detailed information on the use of agricultural inputs, other aspects of farming, and details of phone ownership and phone numbers to conduct the sampling and the intervention.

Household survey. This survey collected extensive information about each household including characteristics of all household members (education, literacy, age, gender, language), land, crop choices, agricultural production (harvests, costs, yields), detailed information on input use (maize, hybrid maize, glyphosate herbicide, and inorganic fertilizer – use over the past two seasons, amount used, source of acquisition), labour on the farm, risk and ambiguity preferences, beliefs about product quality, assets and credit, employment, consumption, and shocks.

Shop survey. The shop survey collected information about the shop owner, characteristics of the shop, and products stocked and sold (details about varieties and brands, where and from whom they purchased them, package sizes, amounts sold, where the products are stored, start, peak, and end of sales, volume of products sold). Through the shop surveys, shop openings and closings were recorded, and new shops were also interviewed.

Hybrid maize seed samples. We collected hybrid maize seed samples at baseline and endline. The goal was to obtain a representative sample of the hybrid maize seed available in the markets visited by the farmers in our sample.[13] For the baseline, we began with a randomly ordered list of all the shops in the market location that were identified in the shop listing exercise for each round. Prior to sample collection, we identified the top 12 varieties of maize in terms of market share in each market hub – this was determined from the shop survey that collected information on each of the varieties sold and the quantities of each during the first shop interviews. The enumeration team aimed to purchase 8 samples of hybrid maize from each market location, and to purchase varieties in the shops that were highest on the list. No maize variety was to be purchased more than once from the same shop.

Once shops with samples were identified, to select a maize variety, the enumerator counted the number of different varieties available in the shop and used a random number table to select a variety. Then, a random number table was again used to select *the type of package* of that variety to purchase out of three different types (if the shop had different types

[13] If asked, enumerators collecting the maize seed samples told shopkeepers that they were students who needed to purchase some inputs for a project. They were asked not to mention anything about input quality and to ensure the owner did not think they were from the government.

of packages).[14] A random number table once again was used to select *the size of the package* if the shop stocked more than one size. Once the package type and size were selected, a random number table was used to select the particular package to purchase, based on the number of packages of that variety, size, and type available in the shop. For each sample purchased, enumerators recorded the variety, package type, the date the package was opened/purchased, the date of expiry, and the sample/package size and price.

For the endline round of sample collection, due to budget constraints and increased testing costs, only two samples of hybrid maize seed were targeted to be purchased from each market location. One sample was to be labeled maize, and the other was to be a package of unlabeled maize. Shops from an updated shop listing exercise were again ordered randomly within market locations and visited accordingly. To select a variety, the enumerator was to count the number of different varieties (within the labeled and unlabeled categories) and select a variety, then a package type, and then the specific package, all using a random number table. Data on the samples collected were recorded in the same manner as well. 382 hybrid maize samples were collected at baseline and 123 at endline.

At baseline, 20 seeds from each sample were randomly selected for testing by pouring the entire sample onto a table that was divided into four quadrants. The seeds were then mixed across the quadrants and a protocol was followed to attempt a random draw of seeds from each quadrant to provide a sample of 20 seeds to send to the laboratory for DNA fingerprinting.[15] Then, using a standard method to determine how genetically "far" a particular seed is from what the package claims it to be, we calculate the Roger's distance from the genetic material measured in each seed and compare it to a reference sample for the genetic material that the variety is supposed to contain (Rogers 1972, see Appendix for full measurement details).[16] A higher value of the Roger's distance means that the seed is less like the variety that the package claims it is.

[14] The first type was an open bulk container, which is a large container or bag that is not sealed, often from a large bag (e.g., 10 kg) that was purchased by the shop. Enumerators were to have the shopkeeper measure out half a kg for purchase. The second package type was a kavera package, which is a small, sealed package that was prepared from a large bag purchased by the shop. The final packaging type was a pre-sealed smaller package that had never been opened, and enumerators aimed to purchase a 2 kg package if available, and a 5 kg package if not.

[15] Genetic testing was conducted by the LGC Genomics Laboratory in the United Kingdom.

[16] For both the baseline and endline, 'reference' hybrid maize seed samples were obtained from breeders where possible, or from the manufacturers. These would serve as the samples to which field samples would be compared for authenticity. We were able to obtain reference samples for most of the varieties collected.

We didn't have reference samples for some of the varieties, so we only have roger's distance for some samples. Table 1 in the Appendix shows that there aren't differences between those with and without data on Roger's distance. [[THIS PARAGRAPH WILL BE A FOOTNOTE AND THE TABLE WILL GO IN THE APPENDIX]]

Appendix Table 1: Baseline Sample Characteristics by the Availability of Reference Sample

	Mean (sd)		Difference in means (p-value)	
	Sample with Roger's distance (1)	Sample without Roger's distance (2)	(1)-(2) (3)	N (4)
Sample collected in week 9	0.023	0.039	0.471	292
	(0.151)	(0.195)		
Sample collected in week 10	0.238	0.234	0.940	292
	(0.421)	(0.426)		
Sample collected in week 11	0.030	0.052	0.376	292
	(0.168)	(0.223)		
Sample collected in week 12	0.019	0.000	0.230	292
	(0.135)	(0.000)		
Sample collected in week 15	0.114	0.130	0.710	292
	(0.317)	(0.338)		
Sample container was a bulk container	0.107	0.092	0.713	290
	(0.298)	(0.291)		
Sample container was re-packaged	0.042	0.066	0.400	290
	(0.195)	(0.250)		
Sample from a distributor	0.259	0.169	0.106	292
	(0.433)	(0.377)		
Sample from Kampala	0.484	0.364	0.064	292
	(0.492)	(0.484)		
Joint F-test			0.489	

Note: Standard deviations are reported in parentheses. P-values for differences in means are derived from regressions of the variable of interest on a dummy variable for a sample with Roger's distance. Stars denote statistical significance as follows: * p < 0.1, ** p < .05, *** p < 0.01.

At endline, the same protocol was followed to select seeds to be tested, however, 50 seeds were first randomly selected to grow in the laboratory. Those 50 seeds were planted and allowed to germinate (sprout). We recorded whether each seed germinated. This enabled measuring the germination rate (proportion of seeds that sprouted). It also enabled the use of a cheaper method of extracting DNA from the seeds at endline (extracting the DNA from leaf clippings rather than from the seeds directly, as was done at baseline).[17] At endline, only

[17] Despite the two methods of DNA extraction differing, because the DNA extracted was of the same quality, geneticists confirmed that the data would be comparable. For details on the two methods, see the appendix.

seeds that germinated had their leaves available for DNA fingerprinting, which is a selected sample. Consequently, we only use germination at endline since only seeds that germinated were tested, creating selection in the sample. We focus instead on germination rates at endline. Germination is a measure of overall quality and is arguably what farmers care most about. While they may have preferences for specific characteristics of seeds, the first priority is whether the seeds germinate at all (Barriga and Fiala, 2018). We believe this is a better measure of reporting quality at endline compared to the genetic testing. At baseline, measuring quality using genetic testing is acceptable since we tested all 50 randomly sampled seeds regardless of whether they would have germinated.

To check for systematic differences in the markets in which we did and did not collect samples, we regress an indicator variable equal to one if a sample was collected from the market on the subsidy indicator variable and market characteristics including the number of shops, amount of maize sold (in kg), prices, and peak months of sales. Results are displayed in Appendix Table 2. Column 1 includes the variables listed above and column 2 adds interactions between the subsidy indicator and each variable. Importantly, treatment does not affect whether a sample was purchased. As expected, samples were more likely to be purchased in markets with more shops and less likely to be purchased in markets where shops' sales are mostly seasonal. Additionally, the higher the proportion of hybrid maize sold in a market, the more likely it is that a sample was purchased there. Looking at column 2, however, none of the interactions with the treatment variable are statistically significant. Consequently, we do not believe that there is selection in markets in which hybrid maize seeds were collected. Consequently, we do not see strong evidence that the markets from which we collected samples at endline are systematically different from those in which we did not and conclude that our analysis in the smaller set of markets in which samples were collected is valid. It is also, of course, necessary since we cannot measure effects on quality or price where samples were not collected.

Appendix Table 2: ML sample collection and baseline market characteristics by Discount

	(1) MLs with available sample collection	(2) MLs with available sample collection
Subsidy	-0.088	-0.620
	(0.121)	(0.693)
Number of retail shops selling ag inputs in ML	0.060***	0.057
	(0.017)	(0.033)

Proportion of shops in ML carrying products with a scratch-off label	-0.179	-0.164
	(0.356)	(0.733)
Proportion of shops in ML having sales of ag inputs seasonal	-0.350*	1.248
	(0.175)	(0.939)
ML avg share of total sales from ag inputs	-0.001	-0.000
	(0.002)	(0.004)
ML avg share of shops with peak sales month in July SS13	0.277*	0.185
	(0.142)	(0.210)
ML avg share of shops with peak sales month in August SS13	0.086	-0.085
	(0.129)	(0.196)
ML avg share of shops with peak sales month in February FS14	-0.081	-0.041
	(0.156)	(0.332)
ML avg share of shops with peak sales month in March FS14	-0.091	-0.064
	(0.083)	(0.123)
ML avg share of hybrid maize in stock	0.567**	1.058***
	(0.179)	(0.215)
ML avg maize price (UXG per kg)	-0.000*	-0.000**
	(0.000)	(0.000)
Subsidy * Number of retail shops selling ag inputs in ML		0.001
		(0.039)
Subsidy * Proportion of shops in ML carrying products with a scratch-off label		0.437
		(1.251)
Subsidy * Proportion of shops in ML having sales of ag inputs seasonal		-1.678
		(1.130)
Subsidy * ML avg share of total sales from ag inputs		0.000
		(0.006)
Subsidy * ML avg share of shops with peak sales month in July SS13		0.199
		(0.204)
Subsidy * ML avg share of shops with peak sales month in Aug SS13		0.307
		(0.184)
Subsidy * ML avg share of shops with peak sales month in Feb FS14		0.315
		(0.669)
Subsidy * ML avg share of shops with peak sales month in Mar FS14		-0.030
		(0.235)
Subsidy * ML avg share of hybrid maize in stock		-0.541*
		(0.246)
Subsidy * ML avg maize price (UXG per kg)		0.000
		(0.000)
Constant	0.489	0.860
	(0.387)	(0.588)
Observations	120	120
R^2	0.216	0.252
Control group mean	0.567	0.567

Standard errors are clustered at the market hub level. Control variables include market location-level average number of shops, average share of shops with EV, average share of shops that have sales of ag inputs seasonal, average share of total sales from agricultural inputs, average share of shops that reported peak month for sales in SS13 is July or August, average share of shops that reported peak month for sales in FS14 is February or March, average share of shops that carried hybrid maize, and average unit price of maize. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5 Regression specification

Our main outcomes are adoption, prices, and quality. For each of these outcomes, we always begin with a simple empirical strategy whereby an outcome variable is regressed on an indicator for a treatment market in which farmers received the subsidy. The specification is:

$$y_{mt} = \beta_0 + \beta_1 S_m + \boldsymbol{\beta_2 X_{m,t0}} + \varepsilon_{mt} \quad (1)$$

where y_m is the outcome variable for market m, S_{m} is equal to one for subsidy markets, and $\boldsymbol{X_{m,t0}}$ is a vector of control variables from baseline. We did not stratify markets for the purposes of randomization, so we do not include strata indicators. For prices and quality, we include a vector of controls from the baseline and midline surveys capturing sample and market level characteristics obtained from the market surveys and sample collection data in some specifications, including the baseline outcome variable.[18] Standard errors are clustered at the level of the market location. For adoption, we use market-level averages of farmer characteristics as well as the baseline outcome variable. We measure prices as the market location average price in UGX per kilogram using the amount that the enumerator paid for the sample when it was collected for testing. We measure quality as the market location average germination rate of samples collected there.

For adoption, we also estimate impacts at the household level and use the following specification:

$$y_{imt} = \beta_0 + \beta_1 S_{\text{m}} + \beta_2 I_c + \boldsymbol{\beta_3 X_{im,t0}} + \beta_4 p_{im,t0} + \varepsilon_{imt}$$

Where i denotes a household. Since farmers were randomized to treatments based on their communities, c, we add a control for the 60 communities that received the information only treatment (interactive voice messages and community meetings and no subsidy) per Muralidharan and Romero (202x), who recommend estimating a fully interacted model. Additionally, since we purposely sampled 7 households in the village who did not own a phone and 3 that did not, we include an indicator for whether the household owned a mobile phone

[18] These include dummies of sample collection week, container type, sample size, seed company where the sample came from, sample variety, place in the store where the sample was taken from, location where the sample is stored, proportion of shops in ML carrying labeled maize (from shop data) and its missing dummy, and average distance from ML to Kampala in km and its missing dummy.

at baseline ($p_{im,t0}$), and we weight the regression with the inverse probability that the household would be sampled.[19] Here, we include strata fixed effects (indicators for each market location, which served as the stratifying variable) and we cluster standard errors at the level of the villages; the level at which randomization was assigned. We measure adoption as a self-report from the primary agricultural decision-maker in the household about whether they used hybrid maize seeds during first season 2017, and whether the hybrid maize was labeled or unlabeled.

3.6. Balance

Household level balance. We find that households across treatment arms look fairly similar to one another. We have very good balance on household demographic characteristics. There are a couple of variables that are imbalanced, but the F-statistic of the joint significance of all the variables indicates that the samples are relatively balanced. Nonetheless, we control for baseline variables in all specifications related to adoption.

Table 3: Baseline Household Demographic Characteristics and Asset Indices

	Mean (sd)			Difference in means (p-value)		
	Control	Information without subsidy	Information with subsidy	(2)-(1)	(3)-(1)	(3)-(2)
	(1)	(2)	(3)	(4)	(5)	(6)
Household head - Age	49.129	48.883	47.609	0.779	0.127	0.336
	(0.831)	(0.856)	(1.289)			
Household head - Male	0.818	0.763	0.834	0.027	0.629	0.084
	(0.022)	(0.023)	(0.039)			
Household head - Completed primary	0.797	0.832	0.819	0.260	0.416	0.763
	(0.088)	(0.089)	(0.092)			
Household head - Literate	0.531	0.555	0.588	0.397	0.057	0.415
	(0.046)	(0.046)	(0.055)			
Decision maker - Age	10.878	11.437	9.667	0.595	0.303	0.261
	(2.714)	(2.740)	(2.961)			
Decision maker - Male	0.148	0.169	0.096	0.183	0.001	0.001
	(0.008)	(0.009)	(0.018)			
Decision maker - Completed primary	0.408	0.409	0.415	0.981	0.790	0.876
	(0.062)	(0.063)	(0.067)			
Decision maker - Literate	0.290	0.332	0.366	0.066	0.003	0.311
	(0.012)	(0.015)	(0.029)			
Number of household members	5.958	5.674	6.522	0.196	0.002	0.003
	(0.549)	(0.552)	(0.577)			
Durables asset index	0.050	0.160	0.191	0.187	0.119	0.802
	(0.061)	(0.069)	(0.107)			

[19] Households with phones are weighted by 1/7 to account for the likelihood of their inclusion in the household sample being 7 out of 10, and households without phones are weighted by 1/3 to account for the likelihood of their inclusion in the household sample being 3 out of 10.

Land asset index	-0.138	-0.116	-0.113	0.767	0.679	0.975
	(0.217)	(0.218)	(0.225)			
Livestock asset index	0.513	0.411	0.569	0.181	0.620	0.249
	(0.054)	(0.058)	(0.124)			
Enterprise asset index	-0.289	-0.207	-0.169	0.362	0.089	0.736
	(0.142)	(0.144)	(0.158)			
All asset index (except land asset)	0.246	0.397	0.411	0.100	0.199	0.928
	(0.077)	(0.078)	(0.147)			
Observations	532	304	244			
Joint F test				0.703	0.117	0.184

Note: The sample is restricted to the market locations in which hybrid maize samples were collected at endline. Standard deviations are reported in parentheses. P-values for differences in means are derived from a regression of the variable on the three experimental arms, an indicator for owning a phone at baseline, and market fixed effects to account for stratification, with standard errors clustered at the community level, the level at which randomization occurred. Missing baseline values are replaced with sample means. All regressions include dummy variables for missing baseline values. Regressions also weight observations according to their probability of selection into the sample based on whether the household owned a phone at baseline. Asset indices were constructed using principal components analysis and report the first principal component. Stars denote statistical significance as follows: * p < 0.1, ** p < .05, *** p < 0.01.

We also note that almost all households in the sample (an average of 93 percent) are growing maize in first season 2014 as well as in the second season of 2013, confirming that the sample targeted (maize growing households) was accurate.

Market level balance. Table 4 examines baseline balance in market characteristics across the treatment and control groups (in markets where samples were collected). Markets have 3.5 shops on average, over 60 percent of shops sell conventional maize seed costing about 4,500 UGX per kilogram and just over 40 percent sell hybrid maize seeds costing about 6,200 UGX per kilogram. Shops generally source their inputs from distributors or wholesalers. The sample is again well-balanced with no statistically significant differences in characteristics.

Table 4: Baseline Market Survey Characteristics by Subsidy Assignment

	Mean (sd)		Difference in means (p-value)
	Control (1)	Subsidy (2)	(1)-(2) (3)
Number of retail shops selling ag inputs in ML	3.618	3.862	0.686
	(0.531)	(0.845)	
Proportion of shops in ML carrying products with a scratch-off label	0.043	0.032	0.806
	(0.034)	(0.024)	
Proportion of shops in ML having sales of ag inputs permanent year round	0.993	1.000	0.348
	(0.007)		
Proportion of shops in ML having sales of ag inputs seasonal	0.007	0.000	0.348
	(0.007)		
ML average share of total sales from ag inputs	84.752	82.411	0.729
	(4.284)	(7.513)	
ML avg share of shops having peak month for maize sales in July SS13	0.177	0.129	0.401
	(0.095)	(0.084)	
ML avg share of shops having peak month for maize sales in August SS13	0.466	0.475	0.898
	(0.071)	(0.098)	

ML avg share of shops having peak month for maize sales in September SS13	0.326	0.382	0.489
	(0.101)	(0.103)	
ML avg share of shops having peak month for maize sales in October SS13	0.031	0.014	0.174
	(0.022)	(0.013)	
ML avg share of shops having peak month for maize sales in February FS14	0.046	0.011	0.314
	(0.034)	(0.008)	
ML avg share of shops having peak month for maize sales in March FS14	0.623	0.590	0.759
	(0.102)	(0.124)	
ML avg share of shops having peak month for maize sales in April FS14	0.331	0.400	0.512
	(0.100)	(0.127)	
ML avg share of OPV maize in stock	0.474	0.527	0.469
	(0.059)	(0.082)	
ML avg share of hybrid maize in stock	0.526	0.473	0.469
	(0.059)	(0.082)	
ML avg maize price (UXG per kg)	4,775.387	4,462.802	0.426
	(258.827)	(483.772)	
ML avg hybrid maize price (UXG per kg)	6,317.832	6,005.025	0.469
	(357.682)	(416.648)	
ML average number of maize varieties in stock	2.847	2.348	0.147
	(0.221)	(0.193)	
ML average proportion of products from retail shop	0.000	0.001	0.346
	(0.000)	(0.001)	
ML average proportion of products from distributor	0.451	0.486	0.762
	(0.145)	(0.119)	
ML average proportion of products from wholesaler	0.367	0.311	0.658
	(0.115)	(0.117)	
ML average proportion of products from other source	0.182	0.202	0.554
	(0.108)	(0.114)	
ML average proportion of products from within this town	0.001	0.000	0.344
	(0.001)	(0.000)	
ML average proportion of products from another town within this district	0.052	0.030	0.342
	(0.024)	(0.026)	
ML average proportion of products from the district town center	0.216	0.220	0.964
	(0.114)	(0.123)	
ML average proportion of products from another district	0.732	0.751	0.858
	(0.111)	(0.126)	
Observations	34	29	
Joint F test			0.915

3.7 Attrition

We examine whether households in our sample attritted between the baseline and endline surveys differentially between the treatment and control groups. We find that both treatments significantly affected the attrition of households from baseline to endline, with households in the treatment arms significantly less likely to attrit. Consequently, we include a specification corrected with inverse probably weighting for adoption.

Table 5: Attrition of HH sample in Subsidy Group

	(1)	(2)

	Attrition from baseline to endline	Attrition from baseline to endline
Information with no subsidy	-0.030*	-0.053**
	(0.016)	(0.025)
Information with subsidy	-0.015	-0.090**
	(0.025)	(0.037)
Information with no subsidy * Household head: Age		0.001
		(0.001)
Information with no subsidy * Household head: Gender		0.045*
		(0.024)
Information with no subsidy * Household head: Completed primary education		-0.004
		(0.016)
Information with no subsidy * Household head: Literacy		-0.010
		(0.031)
Information with no subsidy * PADM: Age		-0.001
		(0.001)
Information with no subsidy * PADM: Gender		-0.038
		(0.026)
Information with no subsidy * PADM: Completed primary level		0.041**
		(0.019)
Information with no subsidy * PADM: Literacy		-0.010
		(0.031)
Information with no subsidy * Household size		-0.000
		(0.002)
Information with no subsidy * Household asset index		0.004
		(0.017)
Information with no subsidy * Land ownership index		0.008
		(0.008)
Information with no subsidy * Livestock asset index		0.016
		(0.013)
Information with no subsidy * Enterprise asset index		-0.005
		(0.010)
Information with no subsidy * All asset index		-0.001
		(0.020)
Information with subsidy * Household head: Age		0.004
		(0.004)
Information with subsidy * Household head: Gender		0.024
		(0.032)
Information with subsidy * Household head: Completed primary education		0.004
		(0.023)
Information with subsidy * Household head: Literacy		-0.000
		(0.078)
Information with subsidy * PADM: Age		-0.003
		(0.004)
Information with subsidy * PADM: Gender		-0.018
		(0.038)
Information with subsidy * PADM: Completed primary level		0.072***
		(0.025)
Information with subsidy * PADM: Literacy		-0.008
		(0.076)
Information with subsidy * Household size		0.001
		(0.003)
Information with subsidy * Household asset index		-0.023**
		(0.011)
Information with subsidy * Land ownership index		0.012

		(0.008)
Information with subsidy * Livestock asset index		-0.005
		(0.010)
Information with subsidy * Enterprise asset index		-0.022**
		(0.010)
Information with subsidy * All asset index		0.029**
		(0.014)
Including controls	No	Yes
Observations	1243	1243
R^2	0.079	0.084
Joint F-test of interaction terms		0.001
Control group mean	0.160	0.160

Notes: The sample is restricted to market locations with sample collection at endline. Outcome is an indicator equal to one if a household that was interviewed at baseline was not interviewed at endline. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

4 Results

4.1 Summary Statistics and Baseline Balance

Household Characteristics. Table 3 displays summary statistics on baseline demographic characteristics of households. First, means are reported for the control group, the information only group, and the information and subsidy group in columns (1) to (3). Next, p-values for whether there are statistically significant differences in means between groups are reported in columns (4) to (6).

On average, the head of the household is approximately 46 years old, about three quarters are male, and about 37 percent have completed primary school. Approximately 65 percent of household heads are literate. The average age of the primary agricultural decision maker in the household is approximately 45 years old, approximately 74 percent are male, and about 37 percent have completed primary school, while approximately 66 percent are literate. This suggests that the household head and primary agricultural decision maker are often the same person, but that sometimes the agricultural decision maker is the spouse or female head of household. However, their education, age, and literacy are very similar. Households across treatment groups have approximately 5.6 members on average. We calculate several asset indices, for household durables, land, livestock, enterprise assets, and finally all of the assets listed above. We use principal components analysis and report the first principal component in each case.

4.2 Joining the product assurance scheme

We now examine the characteristics of varieties that joined the labeled scheme and decided to place labels on their products. We first identified the maize varieties that existed at baseline that would eventually carry the label. We then ran specifications of an indicator that the variety adopted the label regressed on quality, price, and other characteristics of the varieties. Results are presented in table 6 and show that there is only one predictor of selection into the scheme: maize seed quality measured using Roger's distance, a marker of genetic similarity to parent varieties obtained from hybrid seed producers (Rogers 1972, see Appendix for full measurement details). Higher quality companies chose to label their products. This finding is unsurprising given that standard economic models of certification and quality signalling show that higher-quality varieties have more interest in signaling their quality so that they can charge a higher price and differentiate their products. While we could posit that low-quality firms may choose to label their products and increase their prices (and thus profit) in the short-term, theory predicts that they may either still not find it profitable to pay the up-front and the per-label cost and they may also be worried about reputation effects if they do choose to label their products, but farmers later find out that they are poor quality.

Table 6: Characteristics of varieties that joined the product assurance scheme

	(1)	(2)	(3)	(4)
	Labeled product at endline			
Quality	-1.800***	-1.847***	-1.678***	-1.621***
	(0.505)	(0.478)	(0.427)	(0.427)
Unit price of maize (UGX per kg)		0.000***		0.000
		(0.000)		(0.000)
Maize container was 2kg or more		-0.110		-0.088
		(0.091)		(0.101)
Sample container was a bulk container		-0.187		-0.191
		(0.127)		(0.131)
Sample container was a Kavera package		-0.195		-0.303
		(0.176)		(0.232)
Maize sample from a distributor		-0.032		0.081
		(0.097)		(0.129)
Maize sample from Kampala		0.097		-0.095
		(0.077)		(0.102)
Observations	211	210	211	210
R^2	0.069	0.177	0.339	0.367
Including MH Fixed Effects	No	No	Yes	Yes
Including controls	No	Yes	No	Yes

Notes: Standard errors in parentheses. Standard errors are clustered at the ML level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Quality is defined as Roger's Distance ….. explain more here.

4.3 Take-up

Take up of treatment. Almost nobody in the control group villages received the subsidy vouchers, 16 percent of people in the encouragement group (includes communities in treatment markets not assigned to the subsidy treatment) received the subsidy, and about 30 percent of people received the maize subsidy. Very few people redeemed the voucher, however, only 4 percent. This phenomenon is common and in similar authentication systems, almost nobody authenticated their labeled hybrid maize (two percent of the subsidy group). This is a common finding but does not affect the interpretation of the results. In equilibrium, as long as some people authenticate, the scheme still provides a signal.

Table 7: Exposure to treatment interventions at endline

	Mean (sd)			Difference in means (p-value)			
	Control	Information only	Information + subsidy	(2)-(1)	(3)-(1)	(3)-(2)	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
First season 2017							
Attended community meeting	0.002	0.388	0.483	0.000	0.000	0.117	1,082
	(0.044)	(0.488)	(0.501)				
Found meeting helpful	0.002	0.366	0.479	0.000	0.000	0.053	1,082
	(0.044)	(0.482)	(0.501)				
Received voice messages	0.016	0.243	0.365	0.000	0.000	0.004	1,082
	(0.124)	(0.429)	(0.482)				
Interacted with voice messages	0.006	0.169	0.222	0.000	0.000	0.122	1,082
	(0.076)	(0.375)	(0.416)				
Number of calls answered and listened to	3.000	5.178	5.314	0.020	0.001	0.829	160
	(1.633)	(4.178)	(3.961)				
Found calls useful	0.008	0.220	0.320	0.000	0.000	0.013	1,082
	(0.088)	(0.415)	(0.467)				
Received maize coupon	0.002	0.037	0.347	0.000	0.000	0.000	1,082
	(0.044)	(0.190)	(0.477)				
Redeemed maize coupon	0.000	0.007	0.070	0.050	0.000	0.007	1,082
	(0.000)	(0.083)	(0.255)				
Attempted to authenticate labeled maize	0.002	0.007	0.042	0.443	0.000	0.019	1,082
	(0.044)	(0.083)	(0.200)				
Successfully authenticated labeled maize	0.002	0.007	0.038	0.443	0.000	0.020	1,073
	(0.044)	(0.083)	(0.192)				
Second season 2016							
Attended community meeting	0.006	0.404	0.450	0.000	0.000	0.413	1,082
	(0.076)	(0.492)	(0.499)				
Found meeting helpful	0.004	0.391	0.429	0.000	0.000	0.465	1,082
	(0.062)	(0.489)	(0.496)				
Received voice messages	0.008	0.221	0.255	0.000	0.000	0.415	1,082
	(0.088)	(0.415)	(0.437)				

Interacted with voice messages	0.004	0.156	0.143	0.000	0.000	0.665	1,082
	(0.062)	(0.364)	(0.350)				
Number of calls answered and listened to	2.333	4.302	3.928	0.251	0.334	0.540	123
	(3.215)	(3.148)	(3.163)				
Found calls useful	0.006	0.190	0.218	0.000	0.000	0.473	1,082
	(0.076)	(0.393)	(0.414)				
Attempted to authenticate labeled maize	0.000	0.007	0.017	0.049	0.037	0.361	1,082
	(0.000)	(0.083)	(0.129)				
Successfully authenticated labeled maize	0.000	0.007	0.017	0.049	0.036	0.364	1,077
	(0.000)	(0.083)	(0.129)				

Note: The sample is restricted to households in market locations with sample collection. Standard errors are reported in parentheses

4.4 Demand

The first order effect of the subsidy for the labeled products should be an increase in demand. We first estimate market-level impacts of the subsidy on hybrid maize seed adoption. Column 1 of Table 7 estimates equation (1) without any controls, column 2 adds controls (ML average proportion of maize container size at 2kg, ML average proportion of maize container size at 5kg, ML average proportion of maize seeds from distributor, ML average proportion of maize seeds from wholesaler, ML average proportion of maize seeds from Kampala, ML average proportion of shops carrying labeled maize, and ML average distance from Kampala). Column 3 adds dummy variables for each of the 10 market hubs in our sample to account for regional variation, and column 4 includes both market hub dummies and controls. We see a positive and marginally statistically significant impact of the subsidy on the proportion of farmers in a market who used hybrid maize. Coefficients are relatively stable, indicating an approximately five percentage point increase in adoption, over a base of 12; a magnitude of 44 percent, which is quite large.

Table 7: Impacts of Subsidy on ML-level hybrid maize adoption

	(1)	(2)	(3)	(4)
	FS17: Used hybrid maize			
Subsidy	0.050*	0.033	0.054*	0.054**
	(0.025)	(0.023)	(0.026)	(0.021)
Observations	63	63	63	63
R^2	0.387	0.538	0.619	0.700
Including MH Fixed Effects	No	No	Yes	Yes
Including controls	No	Yes	No	Yes
Control group mean	0.123	0.123	0.123	0.123

Notes: Regressions include average baseline adoption across all seasons. Control variables in columns (2) and (4) include ML average proportion of maize container size at 2kg, ML average proportion of maize container size at 5kg, ML average proportion of maize seeds from distributor, ML average proportion of maize seeds from wholesaler, ML

average proportion of maize seeds from Kampala, ML average proportion of shops carrying labeled maize, and ML average distance from Kampala. The missing in control variables are replaced with market hub average. The missing dummy for each control variable is included as well. Standard errors are clustered at the market hub level and reported in parentheses. Stars denote statistical significance as follows: * p < 0.1, ** p < .05, *** p < 0.01.

Note that these estimates are free of potential biases related to within-market selection of farmers purchasing labeled or unlabeled hybrid maize. To examine whether the subsidy improved take up of labeled, unlabeled, or both types of hybrid maize, we must first examine whether farmer characteristics predict the type of maize they purchase. Table 8 shows a regression of an indicator variable for purchasing labeled maize on the subsidy and household characteristics in column 1. The subsidy does increase the likelihood that farmers purchase the labeled maize – as we would expect since the subsidy was for this maize. Household characteristics, however, do not predict the purchase of labeled seed. In column 2, we interact the subsidy dummy with each household characteristic. The subsidy indicator is no longer significant, and none of the interactions are either. We thus proceed with estimating impacts of the subsidy on the two different types of seed at the farmer level.

Table 8: Selection into buying labeled hybrid maize and farmer characteristics by Discount - MLs with Sample Collection

	(1)	(2)
	Farmer purchased labeled hybrid maize in either FS17 or SS16	
Subsidy	0.061***	0.037
	(0.018)	(0.040)
Age of PADM	-0.000	-0.000
	(0.000)	(0.000)
PADM is male	-0.011	-0.006*
	(0.009)	(0.004)
PADM is literate	-0.008	-0.005
	(0.009)	(0.003)
Household size	-0.000	-0.001
	(0.002)	(0.001)
Household asset index	0.004*	0.002
	(0.002)	(0.002)
HH had no phone at baseline	-0.005	-0.002
	(0.008)	(0.006)
Household had access to credit	0.006	0.002
	(0.008)	(0.007)
Subsidy*Age of PADM		-0.000
		(0.001)
Subsidy*PADM is male		-0.030

		(0.044)
Subsidy*PADM is literate		-0.016
		(0.042)
Subsidy*Household size		0.004
		(0.008)
Subsidy*Household asset index		0.010
		(0.011)
Subsidy*HH had no phone at baseline		-0.013
		(0.038)
Subsidy*Household had access to credit		0.017
		(0.032)
Observations	1082	1082
R^2	0.041	0.049
Control group mean	0.007	0.007

Note: The outcome variable has a value of 1 if household used labeled hybrid maize at endline and 0 if household did not. Control variables include primary agricultural decision maker's age, sex, and literacy, household size, household asset index, access to phone and credit at baseline. Missings in baseline farmer characteristics are replaced with market location average. The regressions include dummies for missing in control variables but the coefficients are not shown in the table. Standard errors are clustered at the market location level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We include both the information campaign treatment and the subsidy treatment in the regression. Since there is some imbalance between treatment groups, all columns include baseline controls of household characteristics. Column 1 reports this basic specification, column 2 adds market location fixed effects, and column 3 reports the specification corrected for attrition using inverse-probability weighting. For hybrid maize in general, we see a ten-percentage point increase in the likelihood of hybrid maize adoption (79 percent increase), and a six-percentage point increase in the likelihood of using the labeled seed. In all three columns, coefficients for both outcomes are statistically significant at the one percent level. We also see a weakly significant effect of the subsidy on the use of unlabeled hybrid maize on the order of approximately four percentage points. The information treatment alone had a small and weak effect on the use of labeled maize, but not unlabeled maize.

Table 9: Impacts of Subsidy on household-level hybrid maize adoption

	(1)	(2)	(3)
	FS17: Used hybrid maize		
Information with subsidy	0.105***	0.097***	0.095***
	(0.039)	(0.025)	(0.025)
Information with no subsidy	0.006	0.015	0.014
	(0.033)	(0.021)	(0.021)
Observations	1080	1080	1080
R^2	0.108	0.229	0.231
ML Fixed Effects	No	Yes	Yes
Include inverse probability weights	No	No	Yes
Control group mean	0.126	0.126	0.125
	FS17: Used labeled hybrid maize		
Information with subsidy	0.066***	0.059***	0.058***
	(0.019)	(0.015)	(0.015)
Information with no subsidy	0.007	0.010*	0.010*
	(0.006)	(0.006)	(0.006)
Observations	1080	1080	1080
R^2	0.058	0.123	0.122
ML Fixed Effects	No	Yes	Yes
Include inverse probability weights	No	No	Yes
Control group mean	0.004	0.004	0.005
	FS17: Used unlabeled hybrid maize		
Information with subsidy	0.040	0.038*	0.037*
	(0.033)	(0.020)	(0.020)
Information with no subsidy	-0.000	0.005	0.004
	(0.031)	(0.019)	(0.020)
Observations	1080	1080	1080
R^2	0.080	0.192	0.192
ML Fixed Effects	No	Yes	Yes
Include inverse probability weights	No	No	Yes
Control group mean	0.122	0.122	0.120

Notes: The sample is restricted to market locations with sample collection at endline. Regressions include a dummy variable for whether the household did not own a phone during the first CLE and average baseline adoption across 4 baseline seasons (first season 2014 and 2015 and second season 2013 and 2015). Regressions also control for baseline household head's age, sex; primary agricultural decision maker's age, sex, literacy, and completed primary education; household size, durable asset index, and livestock asset index. When a household is missing a baseline outcome or control value, the missing value is replaced with the mean value for the sample, and a dummy variable is included for all households for which the baseline value is missing. Regressions also include market location dummy variables, and standard errors are clustered at the market location level. Regressions are also weighted for the likelihood of sampling households with and without phones. The weight in column (3) is the phone weight multiplied by the inverse probability of being both the baseline and endline surveys to adjust for attrition. Stars denote statistical significance as follows: * $p < 0.1$, ** $p < .05$, *** $p < 0.01$.

4.4 Prices

We next turn to prices. If demand for products is increasing, we would expect an increase in prices. Table 9 shows that there was indeed an increase in the price per kilogram of hybrid maize seed. This table reports results for all products in the market; labeled and unlabeled. Column (1) reports results from a basic OLS specification. Column (2) reports results from adding market hub fixed effects to the specification, Column (3) adds baseline controls instead, and Column (4) reports results with the inclusion of both controls and market hub fixed effects. The coefficients are consistently signed and of similar magnitude. Overall, the average price of hybrid maize in treated markets was higher by between 9 and 15 percent depending on the specification. This effect size is also relatively large.

Table 9: Impacts of Subsidy on Price of Hybrid Maize (UGX per kg)

	(1)	(2)	(3)	(4)
Subsidy	1384.863***	1248.350***	1230.517**	944.528**
	(402.916)	(368.066)	(478.158)	(405.907)
Observations	63	63	63	63
R^2	0.098	0.504	0.335	0.628
MH Fixed Effects	No	Yes	No	Yes
With controls	No	No	Yes	Yes
Control group mean	7527.206	7527.206	7527.206	7527.206

Notes: Control variables in columns (3) and (4) include ML average proportion of maize container size at 2kg, ML average proportion of maize container size at 5kg, ML average proportion of maize seeds from distributor, ML average proportion of maize seeds from wholesaler, ML average proportion of maize seeds from Kampala, ML average proportion of shops carrying labeled maize, and ML average distance from Kampala. The missings in control variables are replaced with market hub average. The missing dummy for each control variable is included as well. Standard errors are clustered at the market hub level and reported in parentheses. Stars denote statistical significance as follows: * $p < 0.1$, ** $p < .05$, *** $p < 0.01$.

Table 10 then examines differences in prices between labeled and unlabeled products between the treated and untreated markets. We regress the price per kilogram on an indicator for treatment, an indicator for whether the sample is labeled, and the interaction of the two. The specification in each column follows the same format as the table above. First, we observe that prices for unlabeled products in **treated** markets are higher than those in untreated markets. Second, prices for labeled products in **all** markets are higher on average. Third, we cannot reject that prices were different between labeled and unlabeled products in

treated markets. Taken together, we conclude that prices for all hybrid maize increased in treated markets.

Table 10: Impact of Discount on the Maize Sample Price per Kg – labeled vs unlabeled

	(1)	(2)	(3)	(4)
	Sample price per kg			
Subsidy	1369.026*	1397.257**	970.299*	727.846
	(800.914)	(589.418)	(491.180)	(612.478)
Labeled product	79.915	1033.791*	925.168	1361.513
	(572.666)	(575.451)	(800.557)	(850.152)
Subsidy*Labeled	9.943	-498.529	-0.171	82.548
	(907.966)	(749.349)	(650.550)	(599.695)
Controls	No	Yes	No	Yes
Market hub FE	No	Yes	No	Yes
Observations (number of samples)	119	119	119	119
R^2	0.081	0.444	0.807	0.864
Control group mean	7591.667	7591.667	7591.667	7591.667
Subsidy vs. subsidy*Kakasa (p-value)	0.991	0.508	1.000	0.891

Standard errors are clustered at the ML level. The regressions use the sample collection data, which only includes hybrid maize. Control variables include dummies of sample collection week, container type, sample size, seed company where the sample came from, sample variety, place in the store where the sample was taken from, location where the sample is stored, proportion of shops in ML carrying labeled maize (from shop data) and its missing dummy, and average distance from ML to Kampala in km and its missing dummy. In column (5), the list of control variables for Lasso to choose from is the same as the one in columns (3) and (4). * p < 0.10, ** p < 0.05, *** p < 0.01

4.5 Hybrid Maize Quality

Turning finally to maize quality, Table 11 follows the same format as the preceding two tables. The outcome is the market level average of the proportion of seeds in a sample that germinated. While the coefficients are not statistically significant, they are positive. P-values derived from randomization inference are reported in square brackets. A Kolmogorov-Smirnoff test for equality of distributions is rejected with a *p-value* of 0.022 and suggests that the quality of hybrid maize is slightly higher in treated markets. We suspect that the specification is underpowered, but this result provides some evidence that the average quality of hybrid maize improved in treated markets.

Table 11: Impacts of Subsidy on ML-level maize germination

	(1)	(2)	(3)	(4)
	ML Average germination rate			
Subsidy	0.033	0.018	0.039	0.024
S.E.	(0.028)	(0.033)	(0.029)	(0.040)
R.I. p-value	[0.150]	[0.420]	[0.107]	[0.368]
Observations	63	63	63	63
MH Fixed Effects	No	Yes	No	Yes
With controls	No	No	Yes	Yes
Control group mean	0.830	0.830	0.830	0.830

Notes: The randomization inference p-values are implemented with 10000 reps. Control variables in columns (3) and (4) include ML average proportion of maize container size at 2kg, ML average proportion of maize container size at 5kg, ML average proportion of maize seeds from distributor, ML average proportion of maize seeds from wholesaler, ML average proportion of maize seeds from Kampala, ML average proportion of shops carrying labeled maize, and ML average distance from Kampala. The missings in control variables are replaced with market hub average. The missing dummy for each control variable is included as well. Standard errors are clustered at the market hub level and reported in parentheses. Stars denote statistical significance as follows: * $p < 0.1$, ** $p < .05$, *** $p < 0.01$.

Table 12: Kolmogorov–Smirnov equality of distributions test of germination

Group	Largest difference	P-value
No subsidy	0.3803	0.011
Subsidy	-0.0345	0.963
Combined K-S	0.3803	0.022

Notes: The first line tests the hypothesis that germination rate for no-subsidy group contains smaller values than for subsidy group. The second line tests the hypothesis that germination rate for no-subsidy group contains larger values than for subsidy group. The third line shows the approximate asymptotic p-value for the combined test based on the five-term approximation of the asymptotic distributions derived by Smirnov (1933).

Table 13 then separates the treatment effects on labeled and unlabeled products. We use the same outcome – germination – and include an indicator variable for treatment, an indicator for whether the seed came from a labeled sample, and their interaction. We see that germination rates of labeled products are higher in general, and we see suggestive evidence that germination of unlabeled products in treated markets is also higher. Again, we cannot reject that the quality of labeled and unlabeled products was different in treated markets. This is a very similar to the measured germination rate of the Ugandan samples tested by Barriga and Fiala (2018), which was 86%.

Table 13: Impact of Discount on the Maize Germination

	(1)	(2)	(3)	(4)
	Maize seed germination			
Subsidy	0.035	0.027	0.060	0.060*
	(0.036)	(0.034)	(0.039)	(0.036)
Labeled product	0.040	0.059**	0.025	0.100
	(0.026)	(0.029)	(0.051)	(0.070)
Subsidy*Labeled product	-0.016	-0.032	-0.059	-0.063
	(0.044)	(0.043)	(0.049)	(0.052)
Observations	119	119	119	119
R^2	0.039	0.230	0.517	0.636
Including MH Fixed Effects	No	Yes	No	Yes
Including controls	No	No	Yes	Yes
Control group mean	0.828	0.828	0.828	0.828

Notes: Standard errors in parentheses. Each maize sample has 50 maize seeds. Standard errors are clustered at the ML level. The regressions use the sample collection data, which only includes hybrid maize. Control variables include dummies of sample collection week, container type, sample size, seed company where the sample came from, sample variety, place in the store where the sample was taken from, location where the sample is stored, sample unit price per kg, proportion of shops in ML carrying labeled maize (from shop data) and its missing dummy, and average distance from ML to Kampala in km and its missing dummy. In column (5), the list of control variables for Lasso to choose from is the same as the one in columns (3) and (4). * p < 0.10, ** p < 0.05, *** p < 0.01

Taken together, the results in the previous three sub-sections indicate that the subsidy increased demand, prices, and quality for both labeled and unlabeled products, indicating spillovers of the subsidy and product assurance scheme onto unlabeled products. Additionally, prices and quality of labeled products were higher than for unlabeled products in subsidy markets, suggesting that a separating equilibrium formed whereby high-quality varieties could signal their quality and command a higher price so that their investments in quality would be justified.

4.6 Mechanisms

There are two types of potential explanations for our findings. First, there could be extensive margin changes in the composition of varieties available. Poor-quality products may exit the market, new high-quality products may enter the market, or market shares of varieties may change. Alternatively, some shops may exit the market and new ones may enter; perhaps shops selling poor quality products are replaced by those who sell higher quality products. Both could lead to an increase in prices and quality. Second, there could be intensive margin changes whereby varieties change internal processes (such as production processes), or shops change their practices (better storage, for example) that improve quality.

Extensive margin. We first explore whether there are any extensive margin differences in the composition products available on the market. We test whether the number of varieties in a market differ due to the subsidy. As part of the data collection, we asked shops to report the varieties that they sold in the past season, and we sum the number of unique varieties across shops in the same market. Table 14 presents the results, following the same format as previous tables with a base specification, the addition of control variables, the addition of market hub fixed effects, and finally, a specification including both. While none of the coefficients is statistically significant, the results suggest that market power may have become a little more concentrated in treated markets. In the full sample of all markets, we do see consistently significant and negatively signed coefficients. Since the overall quality of products improved slightly, it is possible that low-quality products exited the market, both for labeled and unlabeled products reducing the "lemons" problem.

Table 14: Number of Hybrid Maize Varieties Available in Markets

	(1)	(2)	(3)	(4)
	Number of Hybrid Maize Seed Varieties			
Subsidy	-0.596	-0.220	-0.530	0.062
S.E.	(0.525)	(0.638)	(0.626)	(0.713)
R.I. p-value	[0.182]	[0.643]	[0.197]	[0.879]
Observations	61	61	61	61
Including MH Fixed Effects	No	No	Yes	Yes
Including controls	No	Yes	No	Yes
Control group mean	4.061	4.061	4.061	4.061

Notes: The randomization inference p-values are implemented with 10000 reps. The outcome variable is the market level average of the number of hybrid maize varieties that shops report selling at endline. The regressions use the sample collection data, which only includes hybrid maize. Control variables include dummies of sample collection week, container type, sample size, place in the shop where the sample was taken from, location where the sample is stored, proportion of shops in ML carrying labeled maize (from shop data) and its missing dummy, and average distance from ML to Kampala in km and its missing dummy. Standard errors are clustered at the ML level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We also explore changes in the composition of shops in markets, including the number of shops in a market, the number of shops who enter the market between midline and endline, and the number of shops that exit between midline and endline (using the shop census conducted in each round). The results are contained in Table 15. We find that there are no differences in the number of shops, nor entry and exit of shops between treated and untreated markets.

Table 15: Impacts of Subsidy on ML-level shops

	(1) ML average number of shops	(2) ML average number of shops closed	(3) ML average number of new shops
Subsidy	0.148	0.172	-0.175
	(0.650)	(0.253)	(0.405)
Observations	61	61	61
R^2	0.001	0.008	0.002
Control group mean	4.030	0.364	1.818

Notes: Standard errors are clustered at the market hub level and reported in parentheses. Stars denote statistical significance as follows: * p < 0.1, ** p < .05, *** p < 0.01.

Intensive margin. We now turn to the possibility that there were intensive margin changes that either companies or shops may have made that would improve product quality. We examine whether there are differences across treated and untreated markets on a range of characteristics, first examining product characteristics that the seed company can affect, and then examining the behaviour of shops. Table 16, contains the results of the impact of the subsidy on whether a product carries the product assurance label, whether the product came in a sealed package, and the package size (1kg, half kg, or larger than 1kg). There are no differences in any of these characteristics across treated and untreated markets.

Table 16: Characteristics of Hybrid Maize Varieties affected by companies

	(1) Maize product carries E-tag	(2) Sealed package	(3) Half kg	(4) One kg	(5) Larger than 1kg
Subsidy	0.119	0.118	-0.061	0.168*	-0.015
	(0.107)	(0.092)	(0.057)	(0.091)	(0.050)
Observations	119	119	119	119	119
R^2	0.014	0.019	0.009	0.032	0.001
Control group mean	0.409	0.712	0.136	0.606	0.091

Regressions are clustered at the market level. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 17 examines differences in shop behaviour. Shops can choose where to store a product, from whom to purchase it, and the location from where to purchase it. Improvements in storage and purchase from potentially more trustworthy sources could increase the quality of products sold, as suggested by Barriga and Fiala (2018). However, we find only a slight difference in whether the product was stored on the floor (a poor storage practice) compared to a shelf or platform. There are no differences in whether the shop sourced the product from

a distributor compared to other sources like a wholesaler or informal seller, nor in the location from which the product was purchased (in the main market of that market hub, Kampala, or other sources). These results suggest that intensive margin changes are unlikely to have affected quality and prices of labeled and unlabeled products in subsidy markets.

Table 17: Characteristics of Hybrid Maize Varieties affected by shops

	(7) Sample found on the floor	(1) Source - distributor	(3) Source – other	(4) Purchased from central MH market	(5) Purchased from Kampala	(6) Purchased elsewhere
Subsidy	-0.083*	0.146	-0.150	0.047	-0.009	-0.038
	(0.046)	(0.124)	(0.122)	(0.124)	(0.126)	(0.047)
Observations	119	119	119	119	119	119
R^2	0.022	0.021	0.022	0.002	0.000	0.006
Control group mean	0.121	0.364	0.621	0.424	0.500	0.076

Standard errors clustered at the market level. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Finally, we note that companies did not label all of their products; 25% of companies labeled some but not others. For example, 1kg bags of maize could be labeled while the same variety in a 0.5kg bag may not be and they are often available beside one another in a shop. Product assurance schemes thus may be preferred to quality assurance or minimum quality standards schemes since product quality does not actually need to be tested so they are much cheaper for regulators to implement. The main takeaway is that subsidies for credence goods may not be enough to encourage adoption; credence goods may require an additional signal of quality to overcome the effects of information asymmetries.

[[LOOKING INTO WHAT FARMERS DID – CHANGED WHERE OR FROM WHOM THEY PURCHASED MAIZE]]

5 Conclusion

In this paper, we have shown that, due to the high degree of uncertainty of quality characterizing credence goods, subsidies for these goods may be far more effective when coupled with some form of quality signaling. One method of quality signaling is product assurance, which is when products are certified but not explicitly tested for quality. High-quality firms are more likely to join these schemes because they have more incentive to signal quality and because it would not be profitable for low-quality firms. Consequently, the signal is at least partially credible with at least some high-quality products included in the scheme. Additionally, firms choose which of their products to label – not all high-quality firms may choose to label and not all products that a firm produces are necessarily labeled.

We study this topic in the context of markets for hybrid maize seed in Uganda. The Ugandan government introduced a product assurance scheme called Kakasa, which entailed the placement of scratch labels on bags of hybrid maize seed so that farmers could verify the variety, package size, and expiry date. We introduce a demand shock in randomly selected markets by providing a full subsidy to farmers to try labeled hybrid maize. The subsidy increased demand, prompting an increase in purchases of hybrid maize of 44 percent. However, farmers purchased both labeled and unlabeled seed, indicating increased demand for both. Driven by these demand increases, prices of both types of products also increased. While labeled products were pricier, prices of unlabeled products in treated markets increased and we cannot reject that prices of labeled products differed from unlabeled products. Similarly, the quality of both types of products also increased. While labeled products were of higher quality prior to and after the experiment, by endline, the quality of labeled products was higher than that of unlabeled products, the quality of unlabeled products was higher in treated markets, and we again cannot reject that the quality of labeled products differed compared to unlabeled products in treated markets. The result was a separating equilibrium whereby there were some high-quality, high-priced products and some lower-quality, lower-priced products.

We examine potential channels for these results, including intensive and extensive margin changes. We do not find evidence of intensive margin changes whereby firms improved their processes (no differences in labeled products, package sizes) nor by the behaviour of shop owners (no differences in where a product is stored, where it is sourced, or from whom it is sourced). We do find evidence for extensive margin changes with fewer varieties available in treated markets. Since average quality improved in treated markets, this is consistent with low-quality products exiting treated markets.

We conclude that, despite the limited success of subsidies for credence goods, subsidies can indeed improve take-up if information asymmetries are reduced by providing some type of quality signal. Additionally, product assurance schemes can have spillovers onto unlabeled products and lead to a potentially welfare-improving separating equilibrium where firms can signal high quality and consumers can purchase products that better suit their preferences. Further, we note that the structure of product assurance schemes may even be preferable compared to minimum quality standards and quality assurance. First, firms can benefit from spillovers since they do not have to label all their products. Additionally, since product assurance schemes do not involve laboratory testing, they are far cheaper and logistically easier to implement than both other types of schemes. Consequently, product assurance may be a cost-effective way for governments to regulate the quality of products, especially for credence goods.

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Appendix A: Hybrid Maize Seed Testing Technical Appendix

This technical appendix describes the methodology used for lab tests conducted by LGC Genomics Laboratory in the United Kingdom to determine the genetic composition of hybrid maize seed samples. In this description, reference sample refers to a sample of seeds procured directly from the seed producing company. These seeds are representative of those that are sent to contracted farmers to mass produce the seed for sale in the market. Field sample refers to seeds purchased in a package or from a bin in shops in local markets as part of the surveys. Field samples represent the seed that farmers have available to them in one of their local markets, usually the closest market.

Testing procedures differed slightly at baseline and endline:[1]

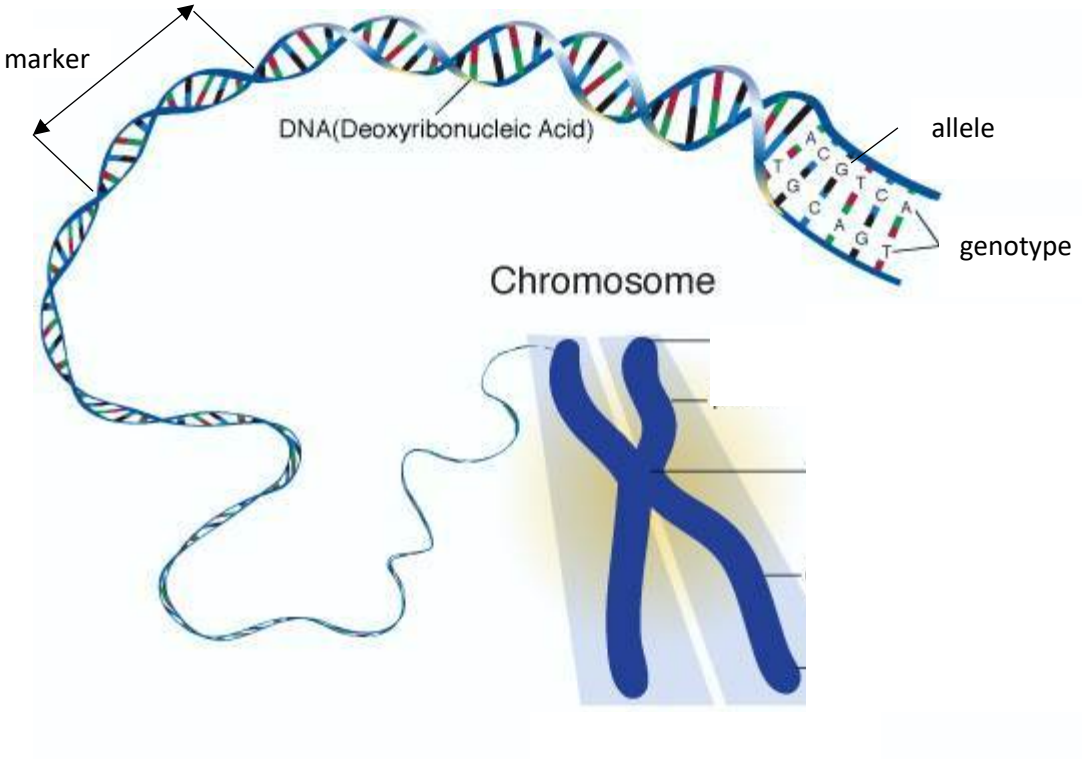
- Baseline: Genetic material was extracted directly from seeds for analysis.
    - From each field sample, 20 seeds were randomly selected. To select these seeds, the entire sample was poured onto a table that was divided into four quadrants using tape. The seeds were then mixed across the quadrants and a protocol was followed to attempt a random draw of seeds from each quadrant in order to provide a sample of 20 seeds for lab analysis.

- Endline: Genetic material was extracted from leaf clippings of seeds that had been planted and grown for analysis.
    - From each field sample, 50 seeds were randomly selected. To select these seeds, the entire sample was poured onto a table that was divided into four quadrants using tape. The seeds were then mixed across the quadrants and a protocol was followed to attempt a random draw of seeds from each quadrant in order to provide a sample of 50 seeds for lab analysis.
    - All 50 seeds selected per field sample were planted and grown in separate pots in a greenhouse by the National Crops Resources Research Institute (NaCRRI) in Kampala, Uganda.
    - Once grown, leaves were clipped from a randomly selected set of 20 seeds that germinated out of the 50 seeds planted. Leaves were clipped when they reached leaf stage 3-4 based on a protocol developed by LGC.[2] Leaf samples were sent to LGC in their "Plant Sample Kit".

[1] The two procedures are equivalent in terms of data produced; leaf clippings are easier to transport and are a cheaper method by which to extract DNA. This is why the procedure was changed between baseline and endline.

[2] LGC. Plant Sample Kit. https://biosearch-cdn.azureedge.net/assetsv6/Plant-leaf-kit.pdf

Figure A1: Illustration of DNA and its components



Source: National Human Genome Research Institute. https://www.genome.gov/genetics-glossary/Chromosome.

- LGC extracted the DNA from both baseline and endline samples and used Kompetitive Allele Specific PCR (KASP), where PCR is Polymerase Chain Reaction (a way of making many copies of DNA, which is needed to do the testing). Figure 1 illustrates the genetic components for this discussion.
    - An **allele** is a heritable unit of a gene that determines a particular feature of an organism. There are four possible alleles in DNA – C, T, A, G (four types of proteins). A **genotype** is a combination of two of these four alleles. Populations with many similar alleles have more similar traits. This indicates that they are closely related and have a recent common ancestor.
    - Genetic **marker** – the location of a string of adjacent genotypes on a **chromosome.**

  In this study, 142 markers were used. Markers were selected based on recommendations for routine low-cost genotyping (Semagn et al. 2012) and also have a good distribution across all chromosomes; these were used in previous genetic studies for seeds in Uganda. LGC provided the genotype for each seed and each marker.

- Data was cleaned and imported into Power-Marker software. For each marker, there are only two possible alleles (two alleles make a genotype). A matrix of allele frequencies was created to note the proportion of each of the two alleles that occur

(proportion of C, T, A, G) in each marker for each seed (*C/2*, *T/2*, *A/2*, and *G/2*). This is the allele frequency – the proportion of times an allele occurs in a seed for a particular marker. See Figure 2. For example, for marker PHM10404_8, there are two possible alleles – C and G. For each seed (listed in each column), the matrix will tell us the proportion of Cs and Gs recorded (essentially, whether they are both Cs, both Gs, or one of each).

Figure A2: Allele frequencies

	A	B	C	D	E	F	G	H	I
1		**Seed**	**5501-52**	**5501-55**	**5501-56**	**5501-59**	**5501-60**	**5501-62**	**5501-63**
2	**Marker**	**Allele**							
3	**PHM10404_8**	C	0.5000	0.5000	0.5000	1.0000	1.0000	0.5000	1.0000
4	**PHM10404_8**	G	0.5000	0.5000	0.5000	0.0000	0.0000	0.5000	0.0000
5	**PHM11985_27**	A	1.0000	1.0000	0.0000	1.0000	1.0000	1.0000	1.0000
6	**PHM11985_27**	G	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
7	**PHM1218_6**	A	0.5000	0.0000	0.0000	0.0000	0.5000	0.0000	0.5000
8	**PHM1218_6**	G	0.5000	1.0000	1.0000	1.0000	0.5000	1.0000	0.5000
9	**PHM12979_9**	A	0.5000	0.5000	0.0000	1.0000	0.5000	1.0000	0.5000
10	**PHM12979_9**	G	0.5000	0.5000	1.0000	0.0000	0.5000	0.0000	0.5000
11	**PHM13673_53**	A	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
12	**PHM13673_53**	G	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
13	**PHM13675_17**	A	0.5000	0.0000	0.0000	0.0000	0.5000	0.5000	0.0000
14	**PHM13675_17**	T	0.5000	1.0000	1.0000	1.0000	0.5000	0.5000	1.0000
15	**PHM13687_14**	A	1.0000	0.0000	0.0000	0.5000	0.0000	0.5000	1.0000
16	**PHM13687_14**	G	0.0000	1.0000	1.0000	0.5000	1.0000	0.5000	0.0000
17	**PHM13696_9**	A	1.0000	0.5000	1.0000	0.5000	1.0000	0.5000	0.5000
18	**PHM13696_9**	G	0.0000	0.5000	0.0000	0.5000	0.0000	0.5000	0.5000

- Then the genetic distance between each seed to every other seed (across field samples and reference samples) is calculated using the Roger's Distance formula:

$$D_R = \frac{1}{L}\sqrt{\sum_{ul}(X_{ul} - Y_{ul})^2/2}$$

where X and Y represent two different seeds populations for the L loci (markers – 142) being studied. Let X_{ul} represent the uth allele frequency (proportion) at the lth locus. Roger's distance provides a measure of the degree of genetic similarity between two seeds. A smaller Roger's distance indicates that two seeds are more similar.

- Calculation of the Roger's distance produces a matrix with the genetic distance (between 0 and 1) between each seed and every other seed (see Figure 3). Note, rows and columns are individual seeds (so it is a symmetric matrix).

Figure A3: Genetic Distance Matrix

	A	CQY	CQZ	CRA	CRB	CRC	CRD	CRE	CRF	CRG	CRH	CRI	CRJ	CRK	CRL	CRM	CRN	CRO	CRP
1	ID	31690-74	31690-76	31690-77	31690-79	31690-81	31690-82	31690-86	31690-89	31690-90	5501-56	5501-85	5503-80	5503-95	5513-77	5513-82	5515-62	5515-65	5516-75
2491	31690-66	0.39513	0.20372	0.41465	0.20851	0.231	0.231	0.19378	0.35564	0.21779	0.52129	0.51939	0.44009	0.44898	0.40379	0.41226	0.33119	0.31119	0.33856
2492	31690-69	0.44455	0.25922	0.43101	0.2132	0.20851	0.19881	0.19881	0.385	0.18329	0.53439	0.52129	0.47673	0.48086	0.40133	0.40986	0.34002	0.27404	0.36388
2493	31690-71	0.385	0.18329	0.44677	0.19881	0.22228	0.2132	0.24752	0.36659	0.20851	0.51748	0.51939	0.4577	0.47465	0.41346	0.41703	0.30639	0.31119	0.33267
2494	31690-74	0	0.36116	0.44455	0.4001	0.4264	0.4264	0.39762	0.43784	0.39513	0.53439	0.53991	0.54265	0.54628	0.45227	0.45985	0.37327	0.38755	0.39513
2495	31690-76	0.36116	0	0.40256	0.20372	0.22668	0.19881	0.22668	0.33563	0.2132	0.52318	0.51748	0.47257	0.47673	0.41106	0.41939	0.31592	0.32057	0.32364
2496	31690-77	0.44455	0.40256	0	0.44677	0.4264	0.44009	0.39762	0.45117	0.43784	0.50394	0.50589	0.49703	0.48901	0.38628	0.41465	0.39886	0.44009	0.41939
2497	31690-79	0.4001	0.20372	0.44677	0	0.20372	0.231	0.231	0.38242	0.18861	0.53624	0.53068	0.46199	0.47047	0.41346	0.41226	0.3371	0.31748	0.32668
2498	31690-81	0.4264	0.22668	0.4264	0.20372	0	0.18861	0.21779	0.37459	0.231	0.53068	0.52129	0.48495	0.49303	0.44344	0.45553	0.32819	0.2881	0.35285
2499	31690-82	0.4264	0.19881	0.44009	0.231	0.18861	0	0.23524	0.36927	0.231	0.55614	0.54718	0.49303	0.50099	0.44344	0.45985	0.34002	0.30151	0.35285
2500	31690-86	0.39762	0.22668	0.39762	0.231	0.21779	0.23524	0	0.36927	0.20372	0.51939	0.50979	0.47673	0.48086	0.39638	0.40501	0.32819	0.2881	0.35285
2501	31690-89	0.43784	0.33563	0.45117	0.38242	0.37459	0.36927	0.36927	0	0.36659	0.53254	0.52694	0.4788	0.48698	0.43671	0.44455	0.39638	0.40986	0.40256
2502	31690-90	0.39513	0.2132	0.43784	0.18861	0.231	0.231	0.20372	0.36659	0	0.51365	0.49603	0.46625	0.47047	0.39886	0.40256	0.32516	0.31119	0.32668
2503	5501-56	0.53439	0.52318	0.50394	0.53624	0.53068	0.55614	0.51939	0.53254	0.51365	0	0.263	0.52881	0.55078	0.46413	0.48189	0.49901	0.53808	0.47361
2504	5501-85	0.53991	0.51748	0.50589	0.53068	0.52129	0.54718	0.50979	0.52694	0.49603	0.263	0	0.53439	0.54537	0.44898	0.47569	0.49703	0.52881	0.45877
2505	5503-80	0.54265	0.47257	0.49703	0.46199	0.48495	0.49303	0.47673	0.4788	0.46625	0.52881	0.53439	0	0.17782	0.46306	0.4577	0.45662	0.48086	0.44455
2506	5503-95	0.54628	0.47673	0.48901	0.47047	0.49303	0.50099	0.48086	0.48698	0.47047	0.55078	0.54537	0.17782	0	0.47152	0.47047	0.46942	0.48901	0.45336
2507	5513-77	0.45227	0.41106	0.38628	0.41346	0.44344	0.44344	0.39638	0.43671	0.39886	0.46413	0.44898	0.46306	0.47152	0	0.20128	0.4333	0.45227	0.39886
2508	5513-82	0.45985	0.41939	0.41465	0.41226	0.45553	0.45985	0.40501	0.44455	0.40256	0.48189	0.47569	0.4577	0.47047	0.20128	0	0.43896	0.45985	0.41226
2509	5515-62	0.37327	0.31592	0.39886	0.3371	0.32819	0.34002	0.32819	0.39638	0.32516	0.49901	0.49703	0.45662	0.46942	0.4333	0.43896	0	0.26858	0.3759
2510	5515-65	0.38755	0.32057	0.44009	0.31748	0.2881	0.30151	0.2881	0.40986	0.31119	0.53808	0.52881	0.48086	0.48901	0.45227	0.45985	0.26858	0	0.385
2511	5516-75	0.39513	0.32364	0.41939	0.32668	0.35285	0.35285	0.35285	0.40256	0.32668	0.47361	0.45877	0.44455	0.45336	0.39886	0.41226	0.3759	0.385	0
2512	5516-76	0.385	0.31119	0.41939	0.32057	0.34147	0.34147	0.33563	0.40256	0.32668	0.48597	0.47569	0.4577	0.46625	0.41346	0.41703	0.36524	0.37459	0.18861
2513	5519-64	0.48698	0.45336	0.47465	0.43784	0.44455	0.43101	0.40744	0.46837	0.42871	0.57363	0.56844	0.52412	0.53531	0.43896	0.43784	0.45445	0.40744	0.47673
2514	5519-76	0.45985	0.4333	0.45553	0.4264	0.42408	0.41939	0.37459	0.44009	0.39262	0.55436	0.54537	0.50296	0.51461	0.42756	0.4264	0.39638	0.37459	0.46625
2515	5520-74	0.43557	0.2881	0.46625	0.231	0.27404	0.26673	0.28116	0.41465	0.2394	0.53808	0.54356	0.47673	0.49703	0.43444	0.43784	0.35145	0.35564	0.37459

- Selecting the reference sample seeds: Each reference sample contains 20 seeds, which also differ from one another somewhat in genetic makeup. As a result, we needed to determine which seeds from the reference sample would serve as the reference seeds for comparison to seeds from the field samples. We calculated the Roger's distance between all seeds within each reference sample, and this produced a symmetric matrix only for reference sample seeds. The two seeds that were closest to each other in terms of genetic distance were selected to serve as the seeds to which field sample seeds would be compared. These are the two reference sample seeds (one in a row and one in a column) that are be included for comparison in Figure 3 (bright green seed IDs are reference sample seeds). All but these two seeds are dropped from the reference sample.
    - Note: As explained by the agronomist at the National Crops Resources Research Institute (NaCRRI) in Uganda, selecting the two most similar reference seeds in terms of Roger's distance is also likely to identify two seeds that are true to type for that variety. He described how these seeds that are most similar are not likely to be very dissimilar to other seeds in the reference sample. They are unlikely to be an outlier pair in terms of genetic makeup.

- Our measure of genetic authenticity is then calculated as the average Rogers Distance between the field sample seed and the two reference sample seeds of the variety that the seed is claimed to be. For example, a seed from a field sample claims to be Longe 11H. There are two Longe 11H reference seeds (Longe11H_seed1 and Longe11H_seed2). The distance between the field sample seed and Longe11H_seed1 is 0.5 and the distance between the field sample seed and Longe11H_seed2 is 0.3. The average distance would be 0.4. This is the continuous measure of genetic distance that is used as the outcome variable at the seed level. Again, lower numbers reflect a greater degree of similarity to the reference sample for the field sample's stated variety.