Do beliefs about agricultural inputs counterfeiting correspond with actual rates of counterfeiting? Evidence from Uganda*

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Abstract

Adoption of modern agricultural inputs in Africa remains low. Counterfeit inputs may contribute: if farmers cannot purchase quality inputs or are unsure about quality, they will not invest (the "lemons" problem). We collect a large sample of herbicide across Uganda; 30% contains less than 75% of the active ingredient advertised. We elicit precise beliefs among numerous Ugandan farmers, who believe 41% of local herbicide is counterfeit. Farmers beliefs about herbicide quality are strongly correlated with true quality available in local markets. Although informed farmers lower the social cost of counterfeiting, the high rate of counterfeiting contributes to the "lemons" problem.

JEL Codes: D84, O13, Q12, Q13, Q16

Key words: agricultural technology adoption, counterfeiting, beliefs, Uganda, Africa

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1 Introduction

Over seventy percent of the African population living under US$1.25 per day is engaged in smallholder farming (IFAD, 2011; Foster and Rosenzweig, 2010). Thus, improving productivity on smallholder farms is essential to reducing poverty rates and to improving food security, as well as numerous other outcomes (Hirvonen and Hoddinott, 2016; Byerlee et al., 2009; Ligon and Sadoulet, 2008; Bravo-Ortega and Lederman, 2005; Ravallion and Chen, 2007; Irz et al., 2001; FAO, 2009). High quality agricultural inputs such as hybrid seeds, fertilizer, and herbicide can enhance productivity, but their use in Africa remains puzzlingly low (Aker, 2011; Kelly et al., 2003; Duflo et al., 2011; Morris et al., 2007; Bold et al., 2015). Several recent studies have documented that returns to input use are indeed high (Duflo et al., 2011; Suri, 2011; Beaman et al., 2013; Bold et al., 2015), and while information campaigns been shown to be beneficial (Duflo et al., 2008), lack of knowledge about returns and proper use is no longer thought to be a sufficient explanation for low rates of adoption. Counterfeit, adulterated, or otherwise low quality inputs may explain the puzzle: if farmers are unable to purchase high quality inputs, or are unsure that the inputs available to them are high quality (if they do not have precise beliefs), they may be less likely to invest (Fairbairn et al., 2017; Tjenstrom et al., 2017; Kilic et al., 2017; Bold, Kaizzi, Svensson, and Yanagizawa-Drott, Bold et al.). While it is commonly thought that counterfeit agricultural inputs are pervasive across Africa, actual rates of counterfeiting and farmers' beliefs about rates of counterfeiting are largely unknown.

Counterfeiting is a classic problem of adverse selection, akin to that of used cars in Akerlof's (1970) paper, "The Market for 'Lemons."' Consumers who cannot observe the quality of a specific item but believe that a fraction of products in the market are low quality (or counterfeit) will have lower willingness to pay for the product, depressing prices. Akerlof (1970) showed that the result of this missing information problem is that producers of higher quality products may be unable to remain in the market, as bad products drive out good, driving down average quality in the market. If consumers' beliefs about average product quality are well informed, the lemons problem is not eliminated, but the social cost of this missing information problem is reduced as risk replaces ambiguity. Consumers then pay a price that better reflects true average product quality, leading

to more efficient markets than would exist if consumers were uninformed about even the fraction of low quality products and thus average product quality.

In this paper, we examine glyphosate herbicide (brand name Round-up), a non-selective herbicide usually used as a labour-saving input in place of hand weeding and the most commonly used modern input in our sample. We study both the true quality of glyphosate herbicide available in rural markets in Uganda as well as farmers' beliefs about herbicide quality. We then examine how tightly correlated farmers beliefs are with true measurements of quality. To our knowledge, we have collected the largest (n=483) and most geographically broad sample of herbicides to date. Samples were tested for their concentration of glyphosate in a laboratory using liquid chromatography, the most advanced measure of quality available. Our sample of farmers is also large and geographically diverse: we collect detailed information from a sample of almost 1,400 rural farmers in Uganda across 25 districts and 120 local markets. Beliefs about herbicide quality are measured in two ways. First, in a traditional household survey, farmers were asked about their previous experiences with herbicide and, using Likert scale qualitative questions, were asked about their impressions of counterfeiting and adulteration in their local market. While these qualitative data can be informative, they are not precise and are thus difficult to compare across farmers and to true rates of counterfeiting. When a farmer responds that he believes "most" herbicide in his market is counterfeit, should the researcher interpret this to mean more than half? More than three-fourths? For a more precise understanding of farmers' beliefs about input quality, respondents were also asked to gather for lab-in-the-field games (an artefactual field experiment (Harrison et al., 2007)). Beliefs were measured quantitatively by eliciting the precise fraction of bottles in the market the farmer believed to be low quality due to counterfeiting or adulteration.

We find first that low quality herbicide is common in Uganda. 32 percent of collected samples contain less than 75 percent of the advertised concentration of glyphosate and another 40 percent of samples contain between 75 and 99 percent of the advertised concentration of glyphosate. Although we cannot distinguish counterfeiting from other causes of low quality (such as adulteration, poor storage, or errors in production), we interpret products whose concentration of active ingredient is well below what is advertised on the label as being misrepresented to consumers, and therefore functionally counterfeit. This result indicates that there is indeed a market for lemons problem in

the agricultural inputs market in Uganda.

We find next that farmers are aware that some herbicide in their local markets is counterfeit or adulterated, and they report lower usage because of low quality inputs. Thirty eight percent of farmers in our sample report ever having used herbicide in the household survey. However, despite low levels of use, farmers are aware of the potential benefits of herbicide. Seventy one percent believe that using herbicide improves yields, and 65 percent believe that using herbicide results in higher earnings. We also find that many farmers believe that counterfeiting does occur: of those who use herbicide, 80 percent believe that it is sometimes counterfeited. Further, farmers are staying out of the market. Of farmers who have recent experience with using herbicide, 31 percent report that they have avoided purchasing herbicide at some point during the past two growing seasons because of fear of counterfeiting. In the lab-in-the-field games, the typical farmer reported he believed 4.07 of ten bottles, or 40.7%, of herbicide in his local market to be counterfeit or adulterated.

Using three different measures of counterfeiting, we find that farmer beliefs regarding counterfeiting are significantly associated with actual rates of counterfeiting. As the fraction of bottles with less than 25 percent concentration of glyphosate[1] increases in the local market, respondents report that they believe more bottles in their local market are counterfeit. As the average ratio of measured concentration to advertised concentration of glyphosate increases, respondents report that they believe a lower percent are counterfeit. As the fraction of bottles with less than 75 percent of the advertised concentration increases, respondents report they believe more bottles have been counterfeited. These results highlight that farmers are informed consumers; this reduces the social cost of counterfeiting, but is also a likely contributor to the low adoption of inputs. To provide a sense of the magnitude of these associations, eliminating counterfeiting in the market with the highest rate of counterfeiting would reduce the proportion of herbicide bottles that farmers believe are counterfeit by 7.5 percentage points. Since, on average, respondents believe that 40.7 percent of herbicide is counterfeit, this is an 18 percent reduction in the perceived average prevalence of counterfeiting. Such a reduction could have a substantial effect on adoption and willingness to pay for herbicide.

In sum, our results indicate that low quality herbicide is pervasive in Uganda and that farmers

[1] The available advertised concentrations are 36.0 and 43.9 percent.

know that much of the herbicide available to them is functionally counterfeit. This suggests that the herbicide market may indeed suffer from a lemons problem, but that inefficiencies in the market are not as severe as they would be if farmers had no sense of the true rates of counterfeit, adulterated, and low quality inputs.

Our study makes three contributions to the literature. First, we test the quality of herbicide from a large and geographically diverse sample using the most advanced laboratory technique available, finding substantial evidence of counterfeiting. Our result adds to the small but growing body of literature documenting input counterfeiting rates in Sub-Saharan Africa (Fairbairn et al., 2017; Tjenstrom et al., 2017; Kilic et al., 2017; Bold, Kaizzi, Svensson, and Yanagizawa-Drott, Bold et al.). We believe ours is the first to study herbicide, the most commonly used modern input in Uganda.

Second, we improve on the measurement of beliefs about the quality of agricultural inputs, demonstrating that precise measurements can be elicited from a less numerate population in a low resource setting. We find that beliefs correlate strongly with actual measures of counterfeiting, validating both the underlying relationship between beliefs and true market conditions, as well as the value of this measurement technique.

Lastly, we contribute to the understanding of how consumer beliefs are formed and demonstrate that farmers beliefs about product quality are strongly correlated with true market conditions. Economists have long assumed that agents hold common information sets, thus differences in their choices must be due to difference in preferences, not beliefs (Manski, 2004). Several papers in the recent literature show that agricultural agents do hold different beliefs (Luseno et al., 2003; Lybbert et al., 2007) and that these beliefs influence agricultural decisions (Giné et al., 2015; Bellemare, 2009a,b, 2012), including decisions about technology adoption (Vargas Hill, 2009; Dillon, 2013; Maertens, 2016). Reviews of the literature on consumers subjective beliefs note that more evidence is needed on whether consumer beliefs are accurate (see Delavande (2014); Delavande et al. (2011); Attanasio (2009)). This paper shows that beliefs are highly correlated with actual rates of counterfeiting in local markets. In this literature, counterfeit antimalarial medication has received much recent attention (see Björkman Nyqvist et al. (2012); Fitzpatrick (2015)). Few

studies have examined beliefs about agricultural input quality, apart from Bold, Kaizzi, Svensson, and Yanagizawa-Drott (Bold et al.), which studies fertilizer. Understanding how beliefs align with actual product quality can shed light on strategies to change the quality of products available. For example, if beliefs about low quality are incorrect, providing correct information to consumers is important. If beliefs about low quality are correct, enforcement measures or a quality guarantee is needed to improve adoption. Our results indicate that policy makers in Uganda would do well to focus attention on programs that improve the true average quality of agricultural inputs available in rural markets.

The paper is organised as follows. Section 2 describes farming in Uganda and provides information about glyphosate herbicide and counterfeiting. Section 3 describes the study setting and design, as well as provides descriptives of the data. Section 4 outlines our estimation strategy. Section 5 presents the results, and Section 6 concludes.

2 Maize Farming, Glyphosate Herbicide, and Counterfeiting

2.1 Maize Farming in Uganda

In this paper, we focus on maize because of its prominence in Ugandan agriculture. Maize is the second most highly produced food crop as well as the fifth most exported crop in Uganda (Uganda Bureau of Statistics, 2014). Most maize is grown by smallholder farmers. Maize is a staple food in Uganda; 90 percent of maize production is used for human consumption within Uganda and the East African region, while 10 percent is used for animal feeds (National Agricultural Research Organization (NARO), 2010). The Government of Uganda has encouraged the development of maize farming by promoting high-quality hybrid maize seed varieties, the use of fertilizers, and minimum or zero-tillage through the use of herbicides in line with the country's Plan for Modernization of Agriculture (National Agricultural Research Organization (NARO), 2010). However, use of these agricultural inputs is extremely low, in part, it is thought, because of a lack of trust in the current inputs supply system due to problems of counterfeiting (Bold et al., 2015).

There are two agricultural growing seasons in Uganda, one beginning around February/March and

another beginning around August/September. The first growing season is usually longer, with more reliable rainfall than the second, and a higher proportion of farmers grow maize during the first season. Maize is most sensitive to weeds in the first three weeks of growth, and weeds should continue to be minimised for the first 10 weeks. In Uganda, both annual and perennial weeds are present. The most common annual weeds in Uganda are *Striga hermonthica* and *Striga asiatica* (National Agricultural Research Organization (NARO), 2010). The seeds of these weeds are dispersed by wind, water, and livestock and can remain viable in soil for up to twenty years. As a result, weeding is important.

2.2 Glyphosate Herbicide

Glyphosate is a nonselective herbicide, meaning it will kill most plants. It is mainly used for weed control prior to planting as it would also kill the crop if applied post-emergence. According to a report by Monitor Deloitte, 75 percent of the market for herbicides in Uganda is represented by glyphosate herbicide (Deloitte, 2014). The main benefit of using herbicide comes from the labour savings it provides in weed management (Service, 2007; National Agricultural Research Organization (NARO), 2010). The alternative in our setting is hand-weeding, which takes substantially longer. In a grow-out trials study comparing maize grown with and without glyphosate herbicide, Ashour et al. (2016) find that time spent on weed management using herbicide is 65 percent of the time spent on weed management without using herbicide.

In Uganda, glyphosate herbicide is available in liquid form that, on the smallholder farms considered here, is generally sprayed using hand-held sprayers. Herbicide sold in this form is then diluted before spraying. The two available concentrations of glyphosate in herbicide in Uganda are 36.0 and 43.9 percent. Glyphosate herbicide is typically sold in 1-liter or half-litre bottles, which are equipped with sealed caps as well as a clear outer wrapping as an additional seal. It is also available for purchase in smaller quantities out of jerry cans, whereby a shop will have a large amount of herbicide available to split into small quantities (farmers often bring a water bottle to fill) (Ashour et al., 2014).

No glyphosate herbicides are manufactured or formulated in Uganda; they are imported from China,

France, Germany, Hong Kong, India, Israel, Kenya, and the United Kingdom (MAAIF, 2014). Distributors purchase the product from importers and sell it to agro-dealers–shops selling agricultural inputs. Shops closer to the capital, Kampala, are more likely to source their supplies directly from distributors. Shops in very remote and rural areas tend to travel to district town centres, large towns outside of their district, or even to Kampala to source their products (Ashour et al., 2014). Because herbicide is not manufactured locally and because of the often long supply chain before the product reaches shops and consumers, the potential for poor supply chain management and for interference is great.

2.3 Herbicide Counterfeiting and Adulteration

The quality and thus efficacy of glyphosate herbicide can be altered in various ways. The focus of this study is on counterfeiting (replacing a genuine product with a different one, or advertising a non-genuine product as genuine) and adulteration (dilution of a genuine product). In Uganda, both counterfeiting and adulteration of agricultural inputs are believed to be widespread, and media reports of counterfeiting are common. In this paper, we do not distinguish between counterfeiting and adulteration since, from a farmer's point of view, the difference cannot be discerned. We will refer to both phenomena as counterfeiting in what follows.

There is little robust evidence on the rates of counterfeiting of agricultural inputs in Africa. The government of Uganda is cognisant of the potential counterfeiting problem. In 2010, the Ministry of Agriculture Animal Industry and Fisheries (MAAIF) estimated that between 10 and 15 percent of the agricultural inputs in the market are counterfeit. The same study remarked that the counterfeiting problem is aggravated by the government's lack of enforcement of the trademark laws, weak corrective measures, and lack of institutional capability (Twinamatsiko et al., 2010). Lack of institutional capacity has resulted in the vast majority of agro-dealers going unregistered with the Agro-Chemicals Control Board,[2] and thus not being subjected to regulation and oversight.

Svensson et al. (2013) conducted tests on fertilizer and hybrid maize in Uganda but did not estimate the rate of herbicide counterfeiting. Across 50 sampled shops, not one sample of UREA fertilizer

[2] In the 2004 and 2008 national agro-input dealer census, only 212 of the 1,328 agro-input dealers were registered (Laker-Ojok, 2009).

contained the recommended amount of nitrogen (46 percent). They also found that 30 percent of the hybrid maize seeds in their sample were counterfeit. In a larger follow-up study, Bold et al. (2015) find that among 369 samples of fertilizer collected from 129 randomly sampled shops in two regions of Uganda, the nitrogen content was 30 percent less than advertised. They also find that less than 50 percent of maize seeds sampled from 30 shops are genuine. Mbowa, Luswata, and Bulegeya (Mbowa et al.) tested 5 types of fertilizer at both the import/wholesale and retail level, and also find evidence of counterfeiting. They find that of the five types tested, Urea was the only fertilizer with an average satisfactory nutrient content. Bamossy and Scammon (1985) report that counterfeit pesticides have been estimated to cause a 15 percent decrease in Kenya's coffee crop yields.

The Deloitte (2014) qualitative study is a comprehensive study providing estimates of agricultural input counterfeiting in Uganda on several agricultural inputs at several levels. They estimate that counterfeiting of agricultural inputs is highest in the herbicide market and is carried out through product mislabelling, label or bottle reuse, expiration date tampering, and label imitation. They estimate that 20 percent of counterfeiting is the result of manufacturers mislabelling products and selling herbicides with lower concentrations of glyphosate than advertised on the label. Agro-dealers and informal salesmen are estimated to be responsible of 60 percent of total counterfeiting by removing labels from authentic products and using them on a lower quality product, or by buying used bottles and refilling them with fake material. Finally, 20 percent of counterfeiting is estimated to be carried out by distributors and agro-dealers by replicating labels and using them for substandard products. There is almost no rigorous evidence about the extent to which different quality issues (counterfeiting, adulteration, poor supply chain policies, etc.) are present in the agricultural sector in Uganda. Although there could be many sources of low quality, as described above, from the point of view of the farmer, what matters is not necessarily the source of the quality, but the extent of the low quality. Our measures of herbicide quality are unable to distinguish the source, which is outside the scope of this paper.

2.4 Farmers' Beliefs about Herbicide Counterfeiting

There is very little literature on farmers' beliefs about counterfeiting of agricultural products. Some work on beliefs regarding counterfeiting has been carried out for antimalarials, however. Björkman Nyqvist et al. (2012) find that 37 percent of the drug shops in their Ugandan sample sell fake antimalarial pills. They also find that the higher the rate of counterfeiting in a particular area, the more respondents report believing that pills were being counterfeited. Evidence on beliefs about agricultural inputs is scarce. Twinamatsiko et al. (2010) conducted interviews with farmer organisation representatives and agro-dealers, and reported that respondents believe that agricultural inputs are counterfeited for a variety of reasons. Scarcity of popular herbicides, for example, makes it possible for agro-dealers to lower the price of the herbicide and attract farmers who are usually not able to identify counterfeited herbicides. Bold et al. (2015) finds that average farmer beliefs on the authenticity of fertilizer in their closest retail shop aligns closely with the average nitrogen content found among samples collected from these shops. The present study builds on this essential finding by extending it to a large sample, for which market-level correlations can be computed.

The media in Uganda have devoted considerable attention to the issue of counterfeit agricultural inputs. Between 2010 and 2015, Ugandan newspapers published 51 articles concerning counterfeit agricultural inputs. These sources provide information to farmers on this phenomenon and likely help shape beliefs regarding the extent and nature of counterfeiting. The media have also reported on ways in which farmers can be more prudent in looking for and avoiding counterfeits. The *Daily Monitor* reported on a Uganda National Agro-input Dealers Association (UNADA) training initiative focusing on how agro-dealers can detect fake inputs (The Daily Monitor, 2011). Also widely publicised are government and private efforts to curb counterfeiting, such as a new police unit formed to detect and punish counterfeit dealers (New Vision, 2014) and a toll-free call centre run by Transparency International Uganda to report counterfeit agro-inputs. This extensive attention to counterfeiting in the media demonstrates that Ugandans have resources by which to become aware of the counterfeiting problem. These news stories likely contribute to farmers' beliefs regarding counterfeiting. Here, we will explore how accurate these beliefs are.

3 Study Setting, Design, and Data

3.1 Setting and Data

The data come from a baseline survey of 2,319 households[3] across major maize-growing areas of Uganda from July 7 through August 15, 2014. The household sample is drawn from 240 villages in 120 market locations (approximately 10 households per village).[4] Market locations are small collections of shops from which households source their agricultural inputs. The sample was selected to cover major maize-growing market hubs (approximately corresponding to districts). See Figure 1 for a map of the market hubs in our sample.

The market locations for this study were selected through a process of stratified random sampling from a list of all market locations obtained from an initial field exercise in each of 10 market hub strata. For each market location, a matched pair of villages was randomly selected (matched on population, distance to market location, and share of households growing maize). Within each village, 10 farming households were randomly sampled for the baseline survey following a community listing exercise and were invited to participate in the detailed beliefs elicitation. The baseline survey collected detailed information on the households' farms, input use, assets, and beliefs on counterfeiting and adulteration of agricultural inputs. See Figure 2 for the structure of the survey.

3.2 Design: Measuring Beliefs

There are several ways to measure respondents' subjective beliefs about the likelihood that herbicide in their area has been adulterated or counterfeited. Delavande et al. (2011) survey the literature on the measurement of subjective beliefs in developing countries and categorise possible methods into three groups: Likert style questions, elicitation of the "most likely" outcome, and a full elicitation of the distribution of beliefs, most often conducted with visual aids. We use two of the three methods in this paper.

[3] Fifty households were dropped from our main sample due to missing or mis-recorded data.

[4] Each market location serves several villages, and in total, our markets serve more than 1,300 villages.

Beliefs on counterfeiting and adulteration were collected in two ways in this study: through questions incorporated in the baseline household surveys and in a separate, more detailed artefactual field experiment (Harrison and List, 2004) during the evening of the household interview. These types of data elicitation techniques are often referred to as lab-in-the-field games. Both the household survey and the field experiment were conducted in the language spoken by the household. First, during the household survey, households that had purchased glyphosate herbicide in the past year were asked whether they were satisfied with the quality of the herbicide they purchased, and if not, why not (reasons included: quality was not what was expected, too expensive, didn't look right, didn't smell right, didn't feel right, didn't kill weeds, and other). Respondents were then also asked whether they thought that the quality of herbicide was ever purposely lowered by cheating (for example, mixing with fake or inferior product, or completely replacing with fake product). If they answered yes, they were then asked what proportion of herbicide in their local market they thought was adulterated or counterfeit, what proportion was adulterated, and what proportion was counterfeit. These questions were scored on a five-point Likert scale (*all*, *most*, *some*, *a little*, and *none*). Respondents were also asked who they thought was responsible for the counterfeiting and adulteration, whether there was anything that could be done about it, whether they had done something about it, and whether they had avoided purchasing herbicide in the past year because they thought it may be counterfeit or adulterated.

We also elicited beliefs in a field laboratory setting.[5] Following the main household interview, all households were invited to attend a group session in the evening where there would be a different type of interviewing and where they would receive an additional appreciation gift (a bar of soap) for attending. Of the 2,319 households interviewed as part of the baseline survey, 1,390 households attended these lab-in-the-field sessions. Eighty-five percent of the primary household survey respondents were also the respondent for the games. We discuss how households that attended the games are different from the full sample in section 3.4. It was important that these questions be asked in a group setting. Eliciting a distribution of beliefs is not an easy task to enumerate, or to respond to. Thus, a successful method is to have a highly trained enumerator provide an example and a demonstration of the elicitation of the distribution of beliefs. This enables respondents to

[5]This type of belief elicitation using lab-in-the-field methods has been used by Luseno et al. (2003), Lybbert et al. (2007), Vargas Hill (2009), Giné et al. (2009), McKenzie et al. (2008), and Giné and Klonner (2006).

understand more easily, and provides more reliable data. Respondents were asked to imagine that 10 farmers like themselves go to their market location and purchase one bottle of herbicide each from a local agricultural inputs shop. They were then asked how many out of the 10 bottles of herbicide they expect not to be genuine (either counterfeited or adulterated). This question was answered privately with individual enumerators. Prior to answering the question, an example was provided to the entire group. A script was read out by the enumeration team's leader that provided an example of the number of farmers in the team leader's village he or she expected would be growing groundnuts this season.[6] Respondents were given the opportunity to ask questions, and then each respondent sat privately with his or her enumerator to answer the question.

3.3 Design: Measuring Counterfeiting and Adulteration

In order to measure the prevalence of counterfeiting in our study areas, glyphosate herbicide samples were collected in September 2014 and tested in a laboratory to assess their authenticity. The goal was to obtain a representative sample of the glyphosate herbicide available in the markets visited by the farmers in our sample. Samples were purchased from rural retail shops representing the 120 rural market locations. In each market location, up to eight herbicide samples were collected, usually as four samples each from two randomly selected shops if each shop had at least four distinct brands. In shops carrying more than four brands, four brands were selected according to market share for that market hub, based on the prior market survey. No brand was sampled more than once from any individual shop, but brands could be repeated within a market location if multiple shops in that market carried the same brands. The approach in each market location thus depended on the particular brands and number of brands of herbicide found in the shops.[7].

Once a brand was selected, sample collectors then selected one of the herbicide bottles available on shelves for sale to customers using a random number table to identify the bottle to purchase. Once the products were purchased, sample collectors recorded basic information about the product (advertised concentration of glyphosate, expiration date, size of bottle, and so on) on a sample

[6]Scripts were read in the local language (either Luganda or Runyakitara). The script was developed alongside team leaders prior to survey training. It was translated from English into local languages by the team leaders, who were native speakers of that particular language. A copy of this script is available on request.

[7]The sample collection protocol and sample tracking sheet are included in the Appendix, Section A

tracking sheet.

The team of sample collectors did not identify themselves as members of a research team, nor did they attempt to pose as farmers. While a mystery-shopper strategy has the advantage of detecting shopkeeper behaviour toward various types of farmers, it would not have been possible for sample collectors to obtain a representative and random sample of inputs available on the market without revealing their identity as nonfarmers.[8]

All samples were tested by the Government Analytical Laboratory, which is part of Uganda's Ministry of Internal Affairs.[9] Each sample was tested in duplicate[10] using high-pressure liquid chromatography with ultraviolet detection to measure the presence of glyphosate in water-soluble granular formulations (Morlier and Tomkins, 1997). This method compares each collected sample to a reference sample[11] and is the standard procedure to determine glyphosate concentration in solution using chromatography (Morlier and Tomkins, 1997). Results were reported as percent glyphosate content[12] and the mean value of the duplicate test results was used for analysis.

3.4 Demographic and Farming Summary Statistics

Table 1 displays demographic summary statistics of all households in our sample (Column 1). Next, because a subsample of households attended the lab-in-the-field games, we split the sample into households who did and did not play the games and show the characteristics of the primary respondent of that particular survey (usually the head of household, Columns 2 and 3), followed by statistical tests of the differences between the two groups (Column 4). Eighty-five percent of the games respondents were the primary agricultural decision maker in the household (who was the primary respondent for the household survey). For those who played the games, there are no differences in the characteristics of respondents who were primary agricultural decision makers and

[8] There is no literature comparing the mystery shopper strategy with other strategies, but other studies have used this approach in the past, including Bold et al. (2015) and Fitzpatrick (2015).

[9] Unopened 1-liter bottles were sent to the laboratory, which used a vibration machine to mix the contents and then measure out a subsample for testing. Three rounds of pre-tests were conducted, involving testing the glyphosate content of herbicide that the research team had diluted to known concentrations.

[10] Three samples were mistakenly tested only once.

[11] The reference sample is a bottle of herbicide that tested for the full concentration of glyphosate compared with an analytical standard glyphosate solution.

[12] In pure acid form.

those who were other types of respondents from the household.

The average age of the primary respondent is 44 years old, and 55 percent of primary respondents are male. Households who participated in the games tended to have younger primary respondents who were more often male. The household was more likely to participate in the games if they were Luganda speaking (the most commonly spoken local language in Uganda) rather than Runyakitara (another prominent local language in Uganda). The majority of all primary respondents completed primary school education, while households who participated in the games were more likely to have completed more schooling after primary school. Overall, 63 percent of primary respondents are literate. The average number of acres of land owned (but not necessarily all cultivated) by households is 2.6, and households who send members to play the games have no more land owned nor assets than households who did not participate in the games.

Table 2 displays summary statistics of farming activity, again showing the full sample (Column 1) and split into households who did and did not play the games (Columns 2 and 3) with statistical tests of the differences between groups (Column 4). Overall, 96 percent of households planted maize during one or both of the last two growing seasons, while only 11 percent used hybrid maize seeds and 11 percent used inorganic fertilizer. Thirty eight percent reported that they had ever used glyphosate herbicide, while 36 percent said they had used it in one of the last two growing seasons. Tests of differences between households who participated in the games and those who did not show that those who participated had higher agricultural knowledge scores[13] and were more likely to have used glyphosate herbicide.

Households who reported using glyphosate herbicide in the last year were asked whether they were satisfied with their purchase; 17 percent were not, and households who were not satisfied with their herbicide were more likely to participate in the games. Of those who were unsatisfied with their herbicide purchase, 71 percent were unsatisfied because the product "did not kill weeds"; 66 percent believe the product was adulterated while 17 percent thought it was counterfeited.[14]

In summary, these statistics suggest that the sample of households who participated in the games are

[13]The agricultural knowledge score is the percent correct on a 'quiz' regarding maize farming practices, whose questions were derived from pamphlets distributed to farmers by the government.

[14]Not shown in table.

younger, are more likely to have male heads of household, speak the primary language in Uganda, and are more educated than those who choose not to participate in the games. Of households who participated in the games, most (85 percent) sent their primary respondent. Households who participated were also more likely to have used glyphosate herbicide in the past year and to be unsatisfied with their purchase. Consequently, our results should not be interpreted as representing the average Ugandan farmer; they should be interpreted bearing in mind that the average respondent on the games was likely more informed than average. Nonetheless, most of this sample comprises people who make agricultural input decisions and are responsible for purchasing agricultural inputs. It is their beliefs that influence adoption.

4 Empirical Specification

To quantify the relationship between farmers' beliefs about counterfeiting and actual counterfeiting, we estimate the following relationship:

$$B_{imh} = f(K_h, X_{imh}, \epsilon_{imh}) \tag{1}$$

B_{imh} represents a farmer's beliefs regarding the authenticity of herbicide, where i denotes the individual, m denotes the farmer's market location, and h denotes the market hub. We assume that a farmer's beliefs about counterfeiting are formed by his own experience buying herbicide in his market location, by discussing counterfeiting with other farmers living nearby, and by exposure to local media. All of these activities happen in a concentrated area, which we denote with m. Market locations are nested under market hubs, h. We focus on two key outcome measures from the lab-in-the-field games: first, respondents' self-reported central belief (the number of bottles of herbicide out of 10 that they most believe are counterfeit); second, an indicator that the respondent reports perfect confidence in the herbicide sold in their area (that is, 1 if a respondent reports that zero bottles of herbicide are counterfeit). We focus on these two measures for three reasons. First, because the qualitative (Likert scale) questions on the extent of counterfeiting were asked only of those who had used herbicide in the past year and also thought some of it had been

counterfeited, they cover only a small and selected sample. The lab-in-the-field games were offered to all respondents and participated in by many. Second, respondents may have different notions of what "some" or "a little" means, making it difficult to compare across respondents how these qualitative beliefs match with actual rates of counterfeiting. By comparison, the lab-in-the-field elicitation offers more precise estimates of what fraction of bottles each respondent believes to be counterfeit. Third, we focus on these two indicators from the quantitative games because they are the easiest to interpret and they clearly elucidate the relationships studied.

We measure counterfeiting, K_h, at the market hub level. We use three measures of counterfeiting: the proportion of samples in a market hub with less than 25 percent measured glyphosate,[15] the average ratio of the measured to the advertised glyphosate concentration in a market hub, and the proportion of samples in a market hub with a measured concentration less than 75 percent of the advertised concentration. The first measure is indicative of absolute levels of glyphosate content, while the latter two are indicative of how close the measured concentration is to the advertised concentration and allows for differences in advertised glyphosate concentrations. Both types of measures are important: the absolute level of glyphosate determines efficacy and whether farmers observe the results of low quality, and the proportion of advertised concentration determines the extent of the "deception" of farmers.

While we are also able to measure counterfeiting rates at the market location level, we face an empirical trade-off: aggregating our testing data to the market location level gives us more geographically specific information, but because relatively few samples were collected per location, the measure is potentially less accurate.[16] In the main specification, we aggregate the testing data to the market hub level. As a robustness check, we instead aggregate the three counterfeiting measures to the market location level.

X_{imh} represents a vector of demographic and agricultural experience controls, including the respondent's age, gender, indicators for literacy, the language of enumeration, an indicator for whether the respondent is the primary agricultural decision maker of the household, agricultural knowledge

[15] The two possible advertised concentrations are 36.0 and 43.9 percent. The percentage of glyphosate is reported as the acid concentration.

[16] While we were able to collect five or more samples for 45 percent of our market locations, we collected one or two for 20 percent of the locations and were unable to collect any samples for 16 percent of locations.

score, household size, an indicator for living with a child under 5 years old, an asset index, and indicators for the number of acres of farming land owned. ϵ_{imh} is a stochastic error term.

In estimating equation (1) we first note that the two outcome variables have different features. The first variable, the number of bottles out of 10 that are believed to be counterfeit, should be thought of as the respondents subjective probability that the input is low quality multiplied by ten. The variable is then naturally censored at 0 (0%) and 10 (100%). Further, because respondents were provided with only discrete values among which to choose (0, 1, 2, ..., 10), they were not able to report a probability between these intervals. Respondents are expected to use rounding, for example, reporting 3 counterfeit bottles if they believe that between 25 and 35% bottles are counterfeit. To account for the interval censored nature of these data, we estimate equation (1) for the first outcome using interval-censored Tobit regression (see Andreoni et al. (2015) for details). The second variable is an indicator for whether the number of bottles believed to be counterfeit is zero. As such, regressions using the second outcome variable are estimated using Probit regression.

Clustering of the standard errors by market location could occur for two reasons. First, the standard errors are clustered in a market location because our explanatory variable of interest, herbicide quality, is measured at the market hub level while a respondent's beliefs may be formed by the quality in his smaller local area. The difference between what we measure (quality at the hub level) and what farmers use to inform their beliefs (quality at the market location level) is akin to measurement error and is perfectly correlated between farmers within market locations. This type of clustering due to using a proxy variable is problematic: thus, clustering the standard errors at the market location level is appropriate, and we do so for both outcome variables.[17]

Second, respondents in a market location could have similar beliefs because they have similar experiences with inputs, talk with each other, and consult the same information sources. It is not immediately clear that this kind of clustering is inherently problematic. If farmers in a market location have correlated personal exposure to counterfeit herbicide, or if talking with other farmers is how information about counterfeiting is spread, then in some sense it is exactly this coherence

[17]Note that provided this measurement error is uncorrelated with other variables in the regression, our coefficient estimates are unbiased (Bellemare, 2015). We do not believe the measurement error due to measuring counterfeiting at the hub level is correlated with farmer demographics and farming experience.

in opinions that we would like to study.[18] If standard errors are clustered at the market location level, we are in a sense obscuring precisely the variation that is most interesting. Thus, although we do cluster standard errors at the market location level, we consider the results a conservative estimate of the standard errors on the effect of the true rate of herbicide counterfeiting on beliefs about counterfeiting.

5 Results

5.1 Farmer Beliefs about Counterfeiting

Table 3 provides summary statistics of farmers' beliefs about the efficacy and quality of herbicide in their local market, again shown for the full sample and for households who chose to participate or not participate, respectively, in the belief measurement games. While beliefs about the efficacy of genuine herbicide were collected from all respondents (Panel A), qualitative assessments about intentional alteration were asked only of those who had used herbicide in the past year (Panel B), and qualitative estimates of the rates of counterfeiting and adulteration were collected from those who thought that herbicide was sometimes counterfeit (Panel C). Quantitative assessments of herbicide alteration were collected from households who chose to participate in the games (Panel D).

Panel A shows that most respondents (71 percent) believe that herbicide increases yields, and the majority (65 percent) believe that genuine herbicide increases earnings. Households who chose to participate in the games are more likely to believe that herbicide increases yields (75 percent compared with 67 percent of households not participating) and are more likely to believe herbicide increases earnings (70 percent, compared with 59 percent). Panel B shows that of those who had used herbicide in the last year, 50 percent say that the subject of adulterated or counterfeit herbicide has come up in conversation with friends and neighbours. Eighty percent say that they believe the quality of herbicide is sometimes altered intentionally (that is, herbicide is sometimes

[18] In an ideal project we would set out to measure precisely how information about counterfeiting spreads and how it is related to local rates of counterfeiting; unfortunately that research question is beyond the scope of this paper. Maertens (2016) provides some good work on this.

counterfeit or adulterated). Households who participated in the games are more likely to talk about alteration and to believe that herbicide is sometimes intentionally altered. Panel C shows that of farmers who believe that herbicide is sometimes intentionally altered, 47 percent think that "all" or "most" is altered, while 39 percent think that "some" is altered and 14 percent think that only "a little" is altered. Households who participated in the games believe that more herbicide has been intentionally altered than do households who chose not to participate in the games.

Panel D shows that for households who participated in the games, respondents believe that on average, 4.07 out of 10 bottles, or 40.7 percent, of herbicide purchased in their local market are counterfeit. Figure 3 shows the distribution of the number of bottles out of 10 that respondents believe are counterfeit in their local market. Ninety respondents (6.47 percent) report perfect confidence (zero bottles counterfeited) in their local market.

5.2 Counterfeiting Prevalence

Table 4 reports the results of laboratory tests of the quality of glyphosate herbicide purchased by the enumeration team in shops in the 10 market hubs in our sample. The mean glyphosate concentration in the 483 samples[19] collected was 32.1 percent, while advertised concentrations were 36.0 or 43.9 percent. Twenty one percent of samples contained less than 25 percent glyphosate, while 38 percent contained between 25 and 36 percent glyphosate, 39 percent contained between 36 and 50 percent glyphosate, and only 2 percent contained more than 50 percent glyphosate.

While the mean level of concentration is informative, we can also examine the laboratory tested concentration compared with the concentration advertised on the bottle.[20] The average sample had a ratio of actual to advertised glyphosate concentration of 0.85, indicating that on average, samples contained less glyphosate than advertised. Thirty one percent of samples contained less than 75 percent of the glyphosate concentration advertised on the bottle, while 40 percent contained 75 to 99 percent of the advertised concentration, 14 percent contained 100 to 110 percent of the advertised concentration, and 15 percent contained more than 110 percent of the concentration

[19] The number of samples was lower than expected because not all shops had herbicide stocked. Some shops had closed down, while others were out of stock.

[20] Among our samples, advertised concentrations of glyphosate herbicide included 36.0 (73.5 percent of samples) and 43.9 percent glyphosate (26.5 percent of samples, all of the WeedMaster brand).

of glyphosate advertised on the bottle. The reason for observing samples with more than the advertised concentration of glyphosate could be due to a commonly used brand (WeedMaster), with an advertised concentration of 43.9 percent glyphosate, being diluted and sold in bottles stating a glyphosate concentration of 36.0 percent (the advertised concentration of all other brands). Alternatively, formulation errors during manufacturing could also be a reason for this observation.

Next, we report summary statistics at the market hub level. Table 4 shows that the quality of herbicide varies by market hub. While only 0 to 25 percent of samples contained less than 75 percent of the advertised concentration of glyphosate in Iganga, Kasese, Masaka, and Mityana, more than 50 percent of samples contained less than 75 percent of the advertised concentration of glyphosate in Hoima and Masindi. Rates of counterfeiting thus vary substantially. These results, coupled with the results regarding farmer beliefs, indicate that there is indeed a market for lemons problem in the agricultural inputs market in Uganda.

5.3 Beliefs and Counterfeiting

Table 5 presents our main results. Panel A displays interval-censored Tobit regressions of the number of bottles out of 10 the respondent believes are counterfeit in her local market on indicators of herbicide authenticity at the market hub level, including demographic and agricultural experience controls and clustering of the standard errors at the market location level. This measure should be interpreted as the percent of bottles counterfeited or adulterated multiplied by ten. As the fraction of bottles with less than 25 percent concentration of glyphosate increases in the market hub, respondents report a belief that more bottles in their local market are counterfeit. As the average ratio of measured glyphosate concentration to advertised concentration increases, respondents report a belief that a lower fraction of bottles are counterfeit. As the fraction of bottles with less than 75 percent of the advertised concentration increases, respondents report believing that more herbicide has been counterfeited or adulterated. Panel B shows marginal effects from analogous Probit regressions using the respondents' report that zero bottles are counterfeit in their local market. The coefficients are all of the opposite sign of those in Panel A, as expected.

To provide a sense of the magnitude of these correlations, eliminating counterfeiting in the market

hub with the highest rate of counterfeiting (56 percent of samples with less than 75 percent of the advertised concentration) would reduce the prevalence of beliefs that herbicide is counterfeit by 7.5 percentage points (0.75 bottles of 10). If, on average, respondents believe that 41 percent of herbicide is counterfeit, this is an 18 percent improvement in beliefs about the average prevalence of counterfeiting. Such a change could have a substantial effect on adoption and willingness to pay for herbicide. These results highlight that farmers are informed consumers. Although informed farmers reduce the social cost of counterfeiting, these results indicate that counterfeiting is still a likely contributor to the low rates of adoption of inputs.

5.4 Robustness Checks

In this section, we briefly discuss several robustness checks that were performed. First, the results on both outcomes are robust to simple estimation using Ordinary Least Squares. Coefficients share the same sign and statistical significance level. OLS is not our preferred specification because it can lead to predicted values outside the bounds of the probability interval (0-10 for our first outcome variable, 0-1 for the second) leading coefficient estimates to be biased and inconsistent, and standard errors are heteroskedastic. However, for our first outcome variable (probability of low quality) no predicted values fall outside the probability interval. For our second outcome variable (probability of perfect quality) only 13.53-14.39% of observations fall outside the probability interval. All standard errors are robust to heteroskedasticity. Second, results are also robust to using other outcome measures, including the minimum and maximum number of bottles out of 10 that respondents report believing to be counterfeit. Third, results are robust to dropping the market hub for which only three samples were collected (Mbale). It is not the case that this market hub with so few samples is driving the results. Results of these three checks are not reported in the paper but are available upon request. We next turn to results using counterfeiting measurement at the market location level. As discussed previously, few samples were collected in each market location, and in some market locations no samples were collected at all. This results in a loss of power, both because with fewer samples per market location compared with the market hub, estimates are less precise, and because for market locations without samples, we lose observations (respondents). However, we report results here to show that they are consistent. Coefficient estimates are smaller in magnitude and are less precise,

as expected, but they have the same sign as those of the hub-level measurements. Table 6 reports the results.

6 Discussion and Conclusion

The issue of whether farmers adopt productivity- and income-enhancing agricultural inputs has received much attention in the literature. Among the numerous hypotheses to explain extremely low adoption in Africa south of the Sahara, quality and authenticity of inputs has only recently attention in the literature. The media, however, have long reported the presence of counterfeit agricultural inputs as well as farmers' beliefs and experiences regarding counterfeiting in an ad-hoc manner. However, beliefs regarding the authenticity of agricultural inputs can help explain adoption decisions in low-income country contexts and thus deserve rigorous treatment.

This paper is one of the first to study the accuracy of consumer beliefs about the authenticity of goods. It is one of the first to collect detailed data on beliefs regarding authenticity, as well as the first to collect a large and geographically widespread sample of agricultural inputs in a country, rigorously tested for authenticity in a laboratory. We elicit beliefs from nearly 1,400 farmers regarding the number of bottles of glyphosate herbicide out of 10 in their local market that they believe to be counterfeit. We also collect almost 500 samples of glyphosate herbicide from 120 markets in all major maize-growing regions of Uganda and test for glyphosate content in a laboratory. These data enable us to correlate farmer beliefs with rates of counterfeiting at the district level, rather than in the aggregate.

We show that glyphosate herbicide is indeed counterfeited in Uganda; 31 percent of samples contained less than 75 percent of the advertised amount of glyphosate. Second, farmers are aware of this phenomenon; 80 percent of farmers believe that herbicide is at least sometimes counterfeited in their local market. Further, farmers do stay out of the market: of farmers reporting recent experience with herbicide, 31 percent report that they have avoided purchasing herbicide in the past year because of counterfeiting. These results indicate that there is a market for lemons problem. Correlations between local rates of counterfeiting and farmers' beliefs reveal that farmers' beliefs regarding the authenticity of the herbicide in their local market are largely accurate. The

higher the rate of measured counterfeiting in the region, the more bottles farmers believe to be counterfeit. The higher the rate of measured counterfeiting in the region, the less likely farmers are to believe that zero of 10 bottles of herbicide are counterfeit. These results highlight that farmers are informed consumers. Although informed consumers reduce the social cost of counterfeiting, the results also indicate that farmers' accurate beliefs regarding the authenticity of herbicide in their local market may contribute to the low adoption of this productivity-enhancing input.

These results have implications both for future research and for policy. Because farmers are cognisant of the benefits of genuine herbicide (70 percent believe that herbicide can increase yields), policy interventions may not need to be directed towards information provision to farmers regarding the benefits of herbicide. Nor would providing information regarding the prevalence of counterfeiting of herbicide help farmers make better decisions. The results suggest that a method by which to guarantee a genuine product to farmers is an appropriate policy intervention. The United States Agency for International Development (USAID) and TetraTech have undertaken a project in this regard (see (Ashour et al., 2014)). Researchers can take heart that farmer beliefs correspond to measured rates of counterfeiting; this result both validates the underlying relationship between beliefs and reality, as well as supports the use of quantitative belief elicitation as a method of measuring beliefs. The results further imply that beliefs may be an important determinant of technology adoption decisions.

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Figures

Figure 1: Map of markets

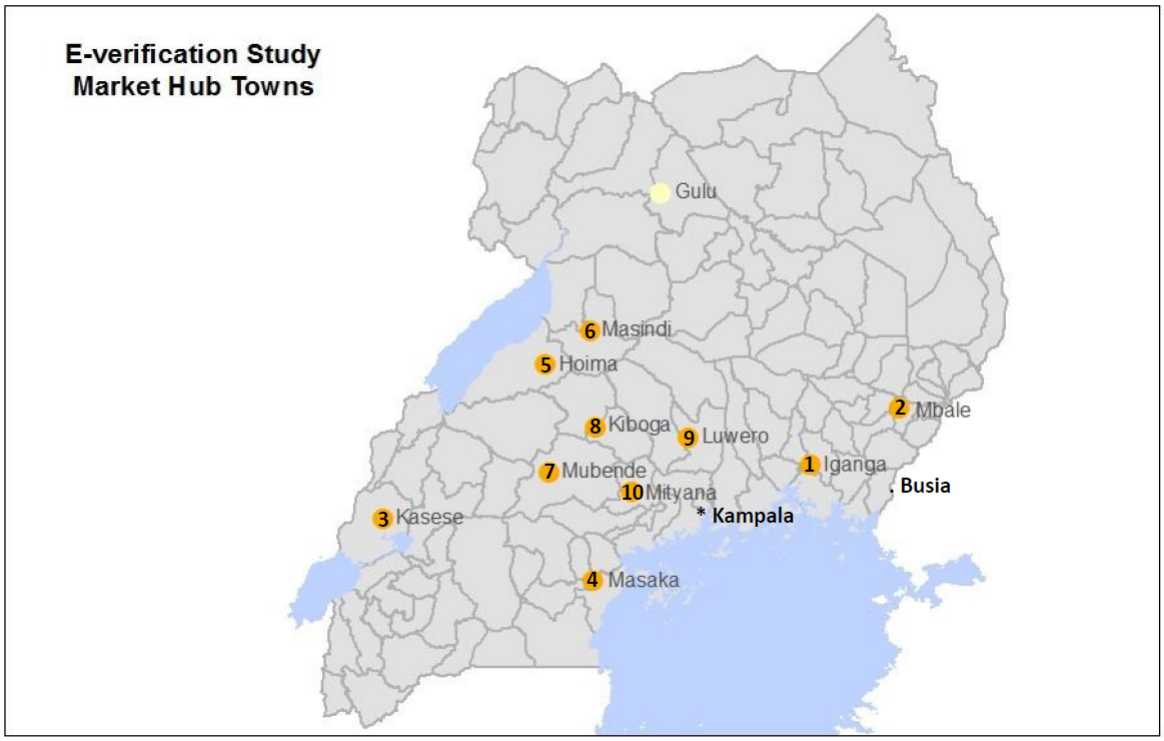


Figure 2: Survey Structure

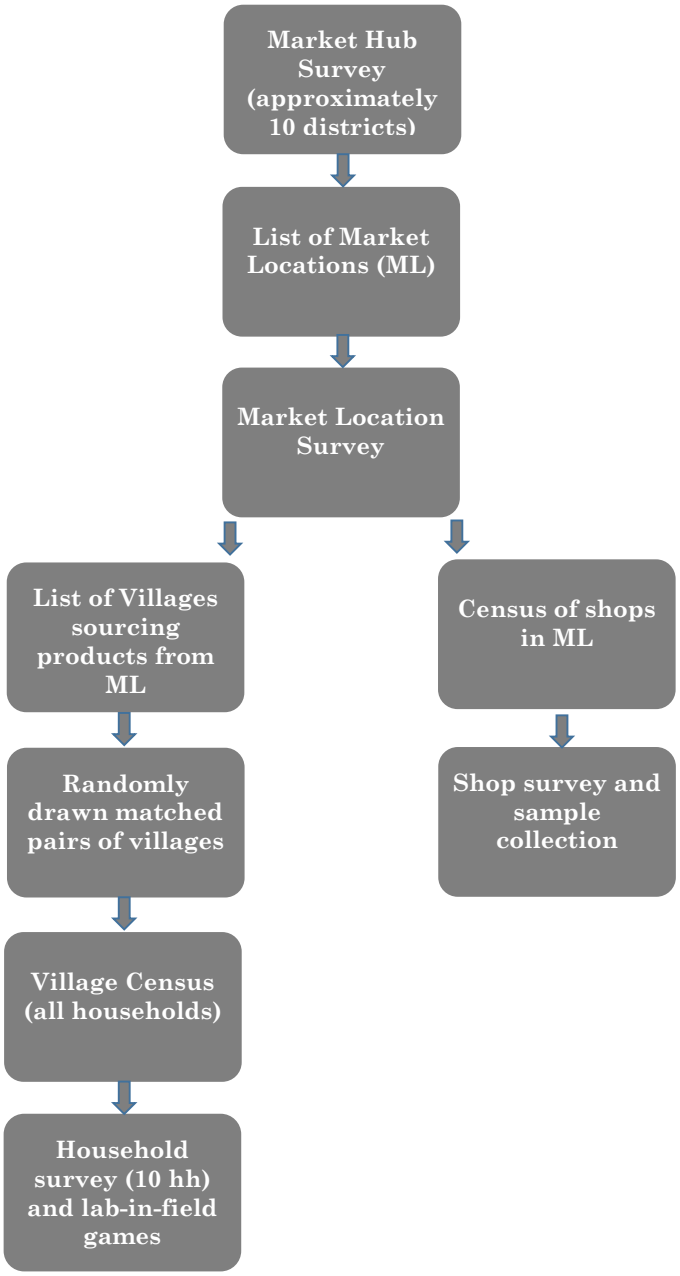
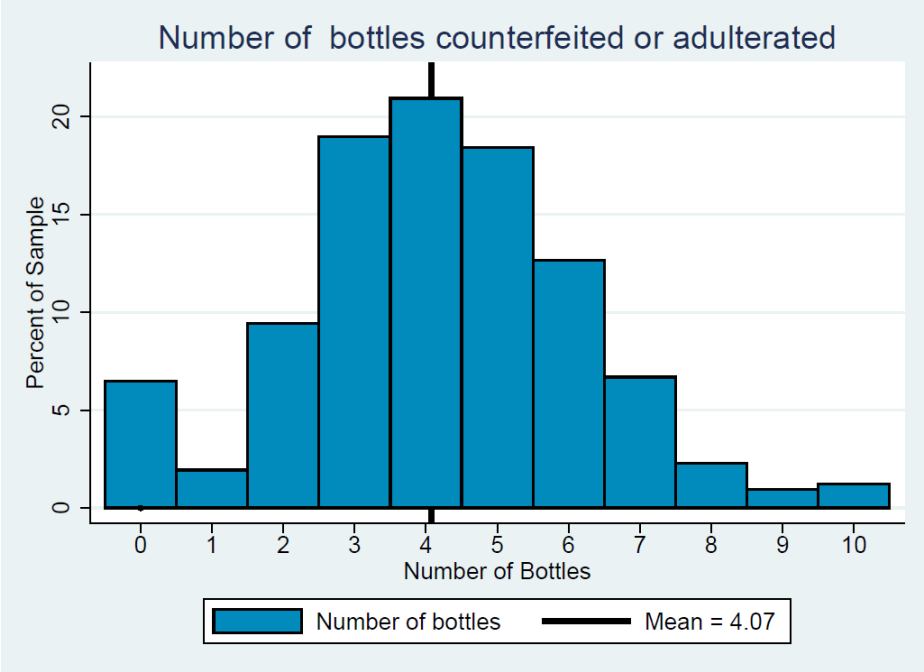


Figure 3: Distribution of number of bottles out of 10 believed counterfeit



Tables

Table 1: Summary statistics: Demographic characteristics

	Full sample	Primary respondent		
		HH did not play games	HH played games	p-value
Age	44.05	46.32	42.54	
	(16.31)	(17.47)	(15.31)	*(0.00)*
Male	0.55	0.49	0.59	
	(0.50)	(0.50)	(0.49)	*(0.00)*
Language of respondent is Luganda	0.61	0.55	0.64	
	(0.49)	(0.50)	(0.48)	*(0.00)*
Language of respondent is Runyakitara	0.28	0.35	0.23	
	(0.45)	(0.48)	(0.42)	*(0.00)*
Language of respondent is other	0.12	0.10	0.13	
	(0.32)	(0.30)	(0.34)	*(0.03)*
No education	0.20	0.25	0.17	
	(0.40)	(0.43)	(0.37)	*(0.00)*
Primary school	0.60	0.57	0.63	
	(0.49)	(0.50)	(0.48)	*(0.01)*
More than primary school	0.20	0.18	0.21	
	(0.40)	(0.38)	(0.41)	*(0.08)*
Literate	0.63	0.58	0.66	
	(0.48)	(0.49)	(0.47)	*(0.00)*
Asset index	0.33	0.32	0.33	
	(0.19)	(0.19)	(0.18)	*(0.08)*
Acres owned	2.59	2.70	2.52	
	(4.46)	(4.93)	(4.11)	*(0.34)*
Number of observations	2,319	929	1,390	

Notes: In Columns 1-3, means with standard deviations in parentheses below are shown for the full sample, and the primary respondents of households who did not and did play the games. The p-value of a two-tailed t-test of the difference in means between households who did and did not play the games is shown in Column 4.

Table 2: Summary statistics: Farming

	Full sample	HH did not play games	HH played games	p-value
Panel A: Asked of all households				
Agricultural knowledge score	8.20	8.09	8.28	
	(2.08)	(2.09)	(2.07)	*(0.04)*
Planted maize in first or second season last year	0.96	0.96	0.96	
	(0.19)	(0.20)	(0.19)	*(0.61)*
Used hybrid seeds in first or second season last year	0.11	0.10	0.12	
	(0.31)	(0.29)	(0.32)	*(0.12)*
Used inorganic fertilizer in first or second season last year	0.11	0.10	0.12	
	(0.32)	(0.31)	(0.33)	*(0.23)*
Ever used herbicide	0.38	0.34	0.41	
	(0.49)	(0.47)	(0.49)	*(0.00)*
Used glyphosate herbicide in first or second season last year	0.36	0.31	0.39	
	(0.48)	(0.46)	(0.49)	*(0.00)*
Number of observations	2,319	929	1,390	
Panel B: Asked of those who used herbicide last year				
Not satisfied with purchase	0.17	0.12	0.20	
	(0.38)	(0.32)	(0.40)	*(0.00)*
Number of observations	805	275	530	
Panel C: Asked of those who were not satisfied with their herbicide purchase				
Not satisfied because "quality not what I expected"	0.29	0.34	0.27	
	(0.45)	(0.48)	(0.45)	*(0.41)*
Not satisfied because "did not kill weeds"	0.71	0.69	0.72	
	(0.45)	(0.47)	(0.45)	*(0.71)*
Number of observations	140	32	108	

Notes: In Columns 1-3, means with standard deviations in parentheses below are shown for the full sample, then split by whether the household did not and did play the games. The p-value of a two-tailed t-test of the difference in means between households who did and did not play the games is shown in Column 4.

Table 3: Summary statistics: Beliefs

	Full sample	HH did not play games	HH played games	p-value
Panel A: Full Sample				
Herbicide increases yields by 100% or more	0.40 (0.49)	0.35 (0.48)	0.44 (0.50)	*(0.00)*
Herbicide increases yields by 50%	0.31 (0.46)	0.32 (0.47)	0.31 (0.46)	*(0.58)*
Herbicide does not increase yields/decreases yields	0.29 (0.45)	0.34 (0.47)	0.25 (0.44)	*(0.00)*
Herbicide increases earnings by 100% or more	0.36 (0.48)	0.32 (0.47)	0.39 (0.49)	*(0.00)*
Herbicide increases earnings by 50%	0.29 (0.45)	0.28 (0.45)	0.30 (0.46)	*(0.14)*
Herbicide does not increase earnings/decreases earnings	0.34 (0.48)	0.41 (0.49)	0.30 (0.46)	*(0.00)*
Number of observations	2,306	923	1,383	
Panel B: Asked of those who used herbicide last year				
Subject of adulteration and counterfeit herbicide has come up in conversation	0.50 (0.50)	0.43 (0.50)	0.53 (0.50)	*(0.01)*
Quality of herbicide is sometimes intentionally altered	0.80 (0.40)	0.78 (0.41)	0.82 (0.39)	*(0.22)*
Number of observations	804	274	530	
Panel C: Asked of those who think herbicide is sometimes altered				
All or most of glyphosate herbicide is adulterated or counterfeited	0.47 (0.50)	0.39 (0.49)	0.51 (0.50)	*(0.01)*
Some of glyphosate herbicide is adulterated or counterfeited	0.39 (0.49)	0.43 (0.50)	0.37 (0.48)	*(0.17)*
A little of glyphosate herbicide is adulterated or counterfeited	0.14 (0.35)	0.18 (0.39)	0.12 (0.32)	*(0.03)*
Number of observations	645	214	431	
Panel D: Asked of households who participated in the games				
Number of bottles not genuine (out of ten)			4.07 (2.02)	
Zero bottles not genuine			0.06 (0.24)	
Number of observations			1,390	

Notes: In Columns 1-3, means with standard deviations in parentheses below are shown for the full sample, then split by whether the household did not and did play the games, respectively. The p-value of a two-tailed t-test of the difference in means between households who did and did not play the games is shown in Column 4.

Table 4: Lab tests of authenticity of herbicide by market hub location

Market hub	**Full sample**	**Iganga**	**Mbale**	**Kasese**	**Masaka**	**Hoima**	**Masindi**	**Mubende**	**Kiboga**	**Luwero**	**Mityana**
Number of samples	483	31	3	26	89	41	59	78	35	59	62
Mean glyphosate concentration	**32.10**	**34.42**	**38.01**	**35.74**	**33.69**	**27.99**	**26.92**	**32.13**	**33.31**	**33.26**	**32.64**
Standard deviation of glyphosate concentration	10.24	8.23	6.04	10.77	7.46	13.86	12.53	10.34	7.60	10.33	8.31
Fraction less than 25%	0.21	0.10	0.00	0.08	0.08	0.51	0.46	0.21	0.09	0.20	0.18
Fraction 25–36%	0.38	0.42	0.33	0.38	0.53	0.15	0.27	0.36	0.54	0.32	0.42
Fraction 36–50%	0.39	0.48	0.67	0.46	0.39	0.29	0.25	0.41	0.34	0.44	0.40
Fraction >50%	0.02	0.00	0.00	0.08	0.00	0.05	0.02	0.03	0.03	0.03	0.00
Mean ratio of stated concentration to actual concentration	**0.85**	**0.88**	**0.94**	**0.97**	**0.90**	**0.74**	**0.73**	**0.84**	**0.88**	**0.86**	**0.86**
Standard deviation of ratio stated concentration to actual concentration	0.27	0.20	0.24	0.29	0.21	0.37	0.33	0.28	0.21	0.27	0.22
Fraction <75% of stated concentration	0.31	0.19	0.33	0.12	0.21	0.56	0.56	0.33	0.31	0.25	0.21
Fraction 75–99% stated concentration	0.40	0.58	0.33	0.38	0.48	0.12	0.20	0.40	0.43	0.41	0.55
Fraction 100–110% stated concentration	0.14	0.16	0.00	0.19	0.11	0.12	0.10	0.14	0.09	0.19	0.16
Fraction >110% stated concentration	0.15	0.06	0.33	0.31	0.19	0.20	0.14	0.13	0.17	0.15	0.08

Note: The two possible advertized concentrations of glyphosate are 36.0 and 43.9 percent.

Table 5: Main results: Farmer beliefs on indicators of quality at the market hub level

	Panel A			Panel B		
	Number of bottles counterfeit	Number of bottles counterfeit	Number of bottles counterfeit	Zero bottles counterfeit	Zero bottles counterfeit	Zero bottles counterfeit
Percentage of bottles less than 25% glyphosate	1.675***			-0.099*		
	(0.642)			(0.051)		
Average ratio of actual to stated concentration		-3.626***			0.187*	
		(1.273)			(0.096)	
Percentage of bottles less than 75% of stated concentration			1.343**			-0.074
			(0.620)			(0.047)
Observations	1,390	1,390	1,390	1,390	1,390	1,390

Notes: Standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Panel A displays interval-censored Tobit regressions of farmers' beliefs about the number of bottles out of 10 that they believe to be counterfeit on market hub-level indicators of herbicide quality. Panel B displays Probit regressions of an indicator for whether farmers believe zero bottles out of ten are counterfeit on market hub-level indicators of herbicide quality. Regressions include demographic controls for respondent age, gender, literacy, indicators for the language of enumeration and whether the respondent is the primary agricultural decision maker, agricultural knowledge score, household size, an indicator for living with a child under 5 years old, an asset index, and indicators for the number of acres of farming land owned. Standard errors are clustered at the market location level.

Table 6: Robustness check: Farmer beliefs on indicators of quality at the market location level

	Panel A			Panel B		
	Number of bottles counterfeit	Number of bottles counterfeit	Number of bottles counterfeit	Zero bottles counterfeit	Zero bottles counterfeit	Zero bottles counterfeit
Percentage of bottles less than 25% glyphosate	0.624**			-0.028		
	(0.244)			(0.023)		
Average ratio of actual to stated concentration		-0.945**			0.045	
		(0.479)			(0.032)	
Percentage of bottles less than 75% of stated concentration			0.479*			-0.025
			(0.256)			(0.022)
Observations	1,176	1,176	1,176	1,176	1,176	1,176

Notes: Standard errors shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Panel A displays interval-censored Tobit regressions of farmers' beliefs about the number of bottles out of 10 that they believe to be counterfeit on market location-level indicators of herbicide quality. Panel B displays Probit regressions of an indicator for whether farmers believe zero bottles out of 10 are counterfeit on market location-level indicators of herbicide quality. Regressions include demographic controls for respondent age, gender, literacy, indicators for the language of enumeration and whether the respondent is the primary agricultural decision maker, agricultural knowledge score, household size, an indicator for living with a child under 5 years old, an asset index, and indicators for the number of acres of farming land owned. Standard errors are clustered at the market location level.

A Appendix: Herbicide Sample Collection Protocol

Retail Shop Sample List

1. Use the sample list to identify which shops to collect samples from in each market location (ML).
2. The first two shops represent the primary source shops. Samples must be obtained from both of the primary source shops.
3. If there is only one shop in the ML, try to collect all eight samples from the one primary source shop.
4. If the required number of samples cannot be collected from the primary source shops, then visit the third shop on the retail shop sample list for that ML and continue down the list until all samples have been collected or there are no more shops in the ML.

Identify which inputs the sample shop carries. Aim to collect eight samples of each input in each ML according to the following guidelines.

Glyphosate Herbicide

1. Brand selection
   (a) Purchase 4 different brands of glyphosate herbicide from each primary source shop. If there is only one shop in the ML, try to purchase up to 8 different brands from that shop. If more than 4 brands are carried in one of the shops (or 8 brands if there is only one shop), purchase the 4 brands that are highest on the market share list for that hub. Make sure that at least 4 samples are from the list of top 10 brands for that market hub even if this means purchasing more than 8 samples from the ML to attain 4 from the list of top 10 brands.
   (b) If one of the shops carries fewer than 4 brands total OR it was not possible to purchase a total of 4 brands from the list of top 10 brands between the two primary source shops, sample the next shop in the same ML following the order of the shop sample list.
   (c) If it's still not possible to reach 8 total brand samples OR 4 brands from the list of top 10 brands with the secondary source shop, sample varieties from the next shop on the sample list and continue sampling shops until 8 brand samples are collected, of which 4 are from the list of top 10 brands, or there are no remaining shops in the ML.
   (d) No brand should be sampled more than once from any individual shop, but brands can be repeated if multiple shops in the same ML carry the same brands.
2. Size selection
   (a) If an individual brand is sold in more than one container size, sample from the 1-liter bottles. If 1-liter bottles are not available then sample from the 0.5-liter bottles.
3. Bottle selection

(a) Randomly select one of the bottles available for sale to customers (you don't need to sample from stores that aren't on the sales floor unless a brand has not been displayed but the shopkeeper has informed you that it is available). Count the number of available bottles for the brand and size you are sampling. Use the random number table to identify which bottle to purchase by counting in the same order until you reach the target number.

4. Sample tracking and labelling

   (a) Record all other information on the sample tracking sheet.

   (b) Label the sample with the sample ID number. Write the label on tape that is firmly affixed to the bottle side (not the lid). Make sure the ink is completely dry so that it won't smudge.

Figure 4: Sample Tracking Sheet

Sample tracking sheet

Market location ID	
Date of sample collection- (dd/mm/yy)	/ / 2014
Sample collector ID	

Maize samples

	Shop ID *From market list*	Shop name	Variety ID	Container type ID 1- Bulk container 2- Kavera package 3- Sealed package >>M5	Date bulk container was opened/kavera packed (dd/mm/yy)	Sample size (kg)	Sample price (UGX)	Date on package (dd/mm/yy)	Date Code	Sample ID (M1-M3)
	M1	**M2**	**M3**	**M3a**	**M4**	**M5**	**M6**	**M7a**	**M7b**	**M9**
1										
2										
3										
4										
5										
6										
7										
8										

M3 CODE

15 Longe 10H
24 PAN 67
19 Longe 6H
3 DK8031
20 Longe 7H
16 Longe 11H
22 Longe 9H
13 KH500-43A
1 DH04
33 YARA 42

H3 CODE

101- 24d
102- Afrisate
1- Agro-sate
103- Butanil
2- Coopersate
106- Field Master
3- Glycel
4- Glyphosate
6- Glyweed
7- Green Fire
105- Green Master
8- Helosate (Twigasate)
121- Herbisate
9- Kalach Extra 70 SG
10- Kalachi 360 SL
107- Kuphosate
11- LB-Glyphosate
12- Liphosate
13- Mamba
108- Milsate
109- No Weed
110- Paraquat
14- Pin-Up
111- Round All
15- Round Up
16- Round Up Turbo
112- Sekasate
113- Supasate
18- Super Weeder
114- Sweep All
19- Sweep W.S
115- Touch Up
20- Touchdown
116- Uphosate
117- Victoria Sate
104- Weed All
23- Weed End
118- Weed Ex
119- Weed Round
24- Weed Up
122- Weedkill
28- Weedmaster
25- Weed-Up
29- Willosate
997- Other

SAMPLE COLLECTOR IDs

1- Ssekibembe Joseph
2- Ayaa Mary Ocaya
3- Ocen Tonny Mark
4- Namugeiyi Feeza S
5- Mwebe Robert
6- Evelyn Kyambadde

DATE CODE
(for questions M7b, H7b, F7b)

1- Date product was packaged
2- Date product was tested
3- Expiration date of product

OTHER CODES
(for questions 4, 5 and 7)

99- Don't know
98- Shopkeeper refused to respond
97- Can't read information on the package
96- No date on package

F3 CODE

1- Sealed package of urea
2- Sealed package of NPK
3- Bulk sample of urea
4- Bulk sample of NPK
5- Kavera package of urea
6- Kavera package of NPK

Herbicide samples

	Shop ID *From market list*	Shop name	Brand ID	Sample size (liters)	Sample price (UGX)	Date on package		Glyphosate contents		Sample ID (H1-H3)
						(dd/mm/yy)	Date code	Quantity	Unit code 1- % 2- g/ml	
	H1	**H2**	**H3**	**H5**	**H6**	**H7a**	**H7b**	**H8**	**H8u**	**H9**
1										
2										
3										
4										
5										
6										
7										
8										
9										
10										
11										

Fertilizer samples

	Shop ID *From market list*	Shop name	Fertilizer type/package type ID	Date bulk container was opened/kavera was packed (dd/mm/yy)	Sample size (kg)	Sample price (UGX)	Date on package		Nitrogen contents (%)	Fertilizer brand name on package	Sample ID (F1-F3)
							(dd/mm/yy)	Date on package			
	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7a**	**F7b**	**F8**	**F8b**	**F9**
1											
2											
3											
4											
5											
6											
7											
8											