Misattribution and uncertainty about beliefs prevent learning

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Abstract

Learning about quality is difficult for many goods, effectively converting experience goods into credence goods. We investigate two mechanisms that prevent learning: misattribution and multiple priors. Misattribution occurs when the process through which inputs are converted to outputs is stochastic, with agents mistakenly ascribing bad outcomes to bad inputs, rather than to other possible causes. An agent holds multiple priors when she is unsure about the likelihoods of good and bad inputs in the marketplace. We develop a Bayesian learning model that incorporates both mechanisms. Our model simulations show that learning about true quality is not possible when both misattribution and multiple priors are present. We apply the model to an important example: fertilizer quality in East African rural markets. We document that farmers in Tanzania and Uganda believe that much of the fertilizer in their local market is counterfeit or adulterated; however, multiple large-scale studies find little evidence to validate that widespread belief. Consistent with model predictions, we find that farmers in areas with more variable precipitation and thus more scope for misattribution believe that more fertilizer in their local market is bad. These farmers also have more uncertainty in their beliefs, evidence of multiple priors. Our results show how incorrect beliefs can persist in equilibrium.

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1 Introduction

Nearly 40% of Sub-Saharan Africa's population lives in extreme poverty, with the majority of the poor employed in agriculture - a low-productivity sector characterized by persistently low crop yields. Improving productivity in agriculture is central to reducing poverty in Sub-Saharan Africa (Byerlee, De Janvry, and Sadoulet, 2009; Bravo-Ortega and Lederman, 2005) and will require increased use of agricultural inputs including fertilizer. Compared to the world average use of nitrogen fertilizer[1] of 70 kilograms per hectare, farmers in Sub-Saharan Africa use only 15 kilograms per hectare. A number of explanations for low fertilizer use have been explored in the literature, including information problems about the technology or its benefits (Foster and Rosenzweig, 2010), heterogeneity in returns (Suri, 2011), credit constraints (Karlan, Osei, Osei-Akoto, and Udry, 2014), and behavioral constraints (Duflo, Kremer, and Robinson, 2011).[2]

Bold et al. (2017) suggest farmers do not use fertilizer because adulteration has reduced its productivity. In their survey in Uganda, farmers on average believed that fertilizer in their local market contained 38% less nitrogen than advertised. In our data from Tanzania and Uganda, 70% and 84% of farmers respectively believe that some fertilizer in their local market is counterfeit or adulterated.[3] Further, farmers report that they are not sure about the rate of counterfeiting and adulteration.

We use a willingness-to-pay experiment in Tanzania to show that farmers who are more

[1]We focus on urea fertilizer, the most commonly used nitrogen-based fertilizer among small farmers and the most widely sold in sub-Saharan Africa (Sanabria, Dimithè, and Alognikou, 2013). Urea is also the fertilizer that has received the most attention in the academic literature on fertilizer quality (Bold, Kaizzi, Svensson, and Yanagizawa-Drott, 2017; Ashour, Gilligan, Hoel, and Karachiwalla, 2019; Michelson, Ellison, Fairbairn, Maertens, and Manyong, 2020). Urea is 46% nitrogen; most small farmer plots are in need of nitrogen and staple cereal cultivation in SSA is often limited by nitrogen availability. Fertilizer blends (in which granules of single nutrients are combined to achieve a desired nutrient composition) and compounds (in which granules themselves contain multiple nutrients) are available in the region, and include different compositions of NPK, DAP, SA, and CAN. These blends and compounds are more expensive and more varied in their composition. Recent studies have found evidence of missing nitrogen and other nutrients in these fertilizer blends and compounds, but these problems are attributable to manufacturing issues rather than adulteration (Sanabria et al., 2013). We discuss these issues in more detail in Section 2.4.

[2]Jack (2013) provides a review of the literature.

[3]Concern about low quality hybrid seeds has been shown to depress willingness-to-pay in Kenya (Langyintuo, Mwangi, Diallo, MacRobert, Dixon, and Bnziger, 2010; Gharib, Palm-Foster, Lybbert, and Messer, 2020).

pessimistic about fertilizer quality are willing to pay less for fertilizer and will pay a higher premium for fertilizer that has been tested in a lab and guaranteed to be perfect quality. Further, we show that certainty in beliefs also affects willingness-to-pay.

Yet these results present a puzzle given that fertilizer in this region is has been shown to have good nitrogen content. The results of numerous large recent studies that randomly sampled fertilizer sellers in Tanzania, Uganda, Malawi, Kenya, Cote d'Ivoire, Ghana, Nigeria, Senegal, and Togo find that fertilizer counterfeiting and adulteration is extremely rare (Michelson et al., 2020; Maertens, Magomba, and Michelson, 2020; Ashour, Billings, Gilligan, Jilani, and Karachiwalla, 2019; Sanabria, Ariga, Fugice, and Mose, 2018a, 2018b).[4] How do incorrect and uncertain beliefs persist in equilibrium?

We build on the work of Bold et al. (2017) and Epstein and Schneider (2007) and develop a Bayesian learning model that incorporates two features that together explain how incorrect and uncertain beliefs can persist: misattribution and multiple priors. Misattribution occurs when an agent mistakenly attributes a bad outcome to a bad input when in fact it was due to bad luck. Misattribution occurs when inputs are linked to outputs stochastically and misattribution can be especially relevant in circumstances when the agent does not fully understand the production function, as is likely for a farmer using fertilizer for the first time. An agent may hold multiple priors when they have some sense of the possible likelihoods of various outcomes, but is not sure of the likelihoods of those outcomes. Rather than believe "50% of fertilizer is fake," the agent may find themselves thinking "I'm not sure what to think. It could be that 50% of fertilizer is fake, but it could be as bad as 90 or 100% fake."[5,6] We simulate the model and show that when misattribution and multiple priors are present, beliefs do not converge to the truth nor to a single prior, even after 100 periods. This likely

[4]Bold et al. (2017) found high rates of fertilizer with significantly lower nitrogen content than advertised in all of their samples but because other larger studies have found no evidence of poor-quality fertilizer, the finding increasingly looks like an outlier in the literature.

[5]Multiple priors are closely related to the idea of ambiguity. Ambiguous beliefs occur when an agent truly has no idea of the likelihood of various outcomes. That concept is not possible to capture mathematically, so theorists introduced the idea of multiple priors, or specific but multiple ideas about possible likelihoods (Gilboa and Schmeidler, 1989).

[6]It is important to note the difference between ambiguous beliefs and ambiguity preferences. Ambiguous beliefs occur when an agent does not know the likelihood of various outcomes. This may or may not affect their decision-making. Ambiguity preferences determine how averse an agent is to situations in which the likelihood of outcomes is not known.

explains low fertilizer use, because incorrect beliefs reduce use through risk aversion (Liu and Huang, 2013; Liu, 2012) and uncertain beliefs reduce use further through ambiguity aversion (Elabed and Carter, 2015; Ward and Singh, 2015; Barham, Chavas, Fitz, Salas, and Schechter, 2014; Ross, Santos, and Capon, 2012; Engle-Warnick, Escobal, and Laszlo, 2007, 2011; Kala, 2019).

The model predicts that beliefs will be more incorrect when outcomes are more variable; more lower tail events are likely to lead to more misattribution. The model also predicts that beliefs will be more uncertain when outcomes are more variable, because it is harder to dismiss a wider range of priors. We test these ideas with precipitation data in Uganda. As predicted, we find that farmers who live in regions with higher historic precipitation variation have more incorrect and more uncertain beliefs.

Goods like fertilizer are often thought of as experience goods, meaning that agents can learn their effects through repeated use. Our model shows that when learning is prevented by misattribution and multiple priors, the good should instead be considered a credence good, meaning that its effects cannot be learned and expectations of effects must be influenced by something other than use. Other credence goods of this type include other agricultural inputs, as well as medication, vaccines, vitamins, car repairs, and education. Consider the flu vaccine. A person may choose to get the flu vaccine, but then become ill. Is that illness certainly flu or could it be some other pathogen? The following year, they may hear in the news that this year's flu vaccine is 75% effective in preventing illness, but recalling their own experience the previous year, they may be unsure of how effective the vaccine will be. Misattribution and multiple priors have prevented their learning, and risk and ambiguity aversion may discourage them from getting the flu shot.

In high-income countries, the quality of credence goods is often ensured through a strong, trusted, and transparent regulatory system. Medical regulatory agencies require large, long clinical trials before authorizing a new drug or vaccine, adverse events are automatically recorded through surveillance systems, and decisions about specific products are discussed in public fora. The quality of education is certified by bodies at the state and national levels. When government certification is not available, crowd-sourced verification springs up through services such as Google and Yelp reviews. By contrast, in low-income countries and communities, government and social media regulatory systems often do not function well, which is how markets like the one for fertilizer in East Africa break down. Our work speaks to the value of a strong and trusted regulatory system.

Our results suggest that programs that provide input subsidies or relax credit constraints alone will not encourage long-term use of fertilizer and other similar goods, because those programs fundamentally rest on the idea that trying a good a few times allows the user to understand and identify its benefits. Because of misattribution and multiple priors, fertilizer and similar goods are not experience goods, so a few uses will not be enough to convince a user of their value. What is needed instead is either a trusted certification program (though these will raise average product costs) or an education program that significantly reduces misattribution.

The paper proceeds as follows: Section 2 describes the setting, context, and data; Section 3 presents the model, simulations, and weather data; Section 4 discusses and concludes.

2 Setting, context, and data

2.1 Maize farming in East Africa

Fertilizers provide essential plant nutrients including nitrogen, phosphorous, and potassium to developing crops. While fertilizers were widely adopted during the Green Revolution by small farmers in much of Asia and Latin America, their use remains low in Sub-Saharan Africa. Our focus in the paper is urea fertilizer, a single-nutrient industrially produced fertilizer, 46% nitrogen by weight and among the most common and widely used fertilizers in the world.

Sheahan and Barrett (2017) document that only 16.9% of Tanzanian small farm households use fertilizer and only 3.2% do in Uganda. Low use of fertilizers directly contributes to widespread problems of low crop yields and high rates of poverty and food insecurity

(Tittonell and Giller, 2013; Dzanku, Jirström, and Marstorp, 2015). For example, while maize is East Africa's most important staple cereal crop (World Bank, 2009), critical as a food and feed source as well as as a source of income and employment, yields remain extremely low in in the region (Dorosh, Wang, You, and Schmidt, 2012; Diao, Fan, Headey, Johnson, Pratt, and Yu, 2008): yields are approximately two metric tons per hectare, well below estimated regional yield ceilings of 4-5 metric tons per hectare (Tittonell and Giller, 2013).[7]

2.2 Our data sources

Our survey data come from two primary sources. The first we collected in the Morogoro region of Tanzania in August 2019: 349 farmers in 18 villages. The second data set is a survey collected by the International Food Policy Research Institute (IFPRI) in July-August 2014 (Ashour, Billings, Gilligan, and Karachiwalla, 2015). The Uganda sample is a representative household survey of the maize growing regions of Uganda, and includes 1388 households in 239 villages.[8]

Table 1 shows farming summary statistics for the Tanzania data. On average, farmers cultivated 3 acres in the previous long rains growing season, 34 percent had ever purchased fertilizer, and only 12 percent reported using fertilizer in the last primary growing season. Table 2 shows similar descriptives for the Uganda data. On average, farmers owned 2.6 acres and 15 percent had ever used fertilizer; 11 percent reported having used fertilizer in the most recent primary growing season.

These two data sets share a special and distinguishing feature: both measure farmers' beliefs about the prevalence of poor quality fertilizer in their respective markets. Both surveys use a similar strategy for eliciting these beliefs. Enumerators asked farmers to imagine that ten farmers visited their local fertilizer seller and that each farmer purchased a bag of urea

[7] For comparison, maize yields in the United States are around 11.5 metric tons per hectare.

[8] The Uganda data are a baseline for a multi-year impact evaluation by IFPRI. Details are available in (Ashour et al., 2019). The full Uganda sample includes 2475 households; however, we restrict the sample to only the 1388 for which we have measurements of their quantitative beliefs about fertilizer quality.

Table 1: Farming summary statistics: Tanzania

	(1)
	mean/sd
Acres cultivated in 2019	3.02
	(2.06)
Ever purchased mineral fertilizer	0.34
	(0.48)
Used mineral fertilizer in 2019	0.12
	(0.32)
Observations	349

Table 2: Farming summary statistics: Uganda

	(1)
	mean/sd
Acres owned 2014	2.57
	(3.96)
Ever used mineral fertilizer	0.15
	(0.35)
Used mineral fertilzer in 2014 first season	0.11
	(0.31)
Observations	1388

fertilizer. The farmer was then asked how many of these ten bags of fertilizer would be good quality or bad quality (counterfeit or adulterated). The farmer's report of how many bags of ten are likely to be bad is a measure of the farmer's belief about the risk of buying bad fertilizer.

In the Tanzanian survey, farmers were asked to qualitatively report their certainty in their belief about the prevalence of bad fertilizer: "completely sure," "mostly sure," "not sure," or "I have no idea, I'm just guessing." The Uganda survey includes a quantitative measure of how many outcomes the farmer thought possible, and the likelihood of each outcome. After asking how many of ten farmers would return home with a bag of poor quality fertilizer, enumerators asked the farmers the maximum number of farmers that would come home with bad fertilizer and the minimum number - eliciting the range of outcomes the farmer thought possible. The enumerator then showed the farmer a card with eleven bins, with the possible range they identified uncovered. The enumerator gave the farmer 15 beans to distribute between the minimum and maximum outcomes they had reported, and instructed the farmer to put more beans in the bins they thought more likely.[9]

2.3 Beliefs about fertilizer quality

Recent studies have established that farmers in Sub-Saharan Africa believe there is poor quality urea fertilizer in their local markets. Michelson et al. (2020) find 36% of surveyed farmers (in a sample of 164 farmers) report urea adulteration is a problem in the market in Morogoro Region, Tanzania. Bold et al. (2017)'s sample of Ugandan farmers reported that urea fertilizer available in their local markets was missing 38% of its nutrients on average.[10] Reports from the International Fertilizer Development Center (Sanabria et al., 2013, p. 39) conducted in countries in East and West Africa note that farmer beliefs about the prevalence of adulterated urea are widespread but without scientific support.

Fertilizer is sold by weight and is required to be in accordance with national standards related to nutrient content. Urea fertilizer, for example is 46% nitrogen by weight. Urea fertilizer with less than 45% nitrogen is considered out of compliance based on regional regulatory standards in East Africa. Nitrogen can be missing due to problems in manufacturing or due to adulteration or counterfeiting. Adulteration is when fertilizer is mixed with non-fertilizer material in sufficient quantities to dilute its agronomic effectiveness - the foreign material could be agronomically inert substances like small pebbles; the material could also be something with potentially deleterious effects like rock salt. Counterfeiting is an extreme form of adulteration: a counterfeit bag of fertilizer is a bag of completely non-fertilizer material (pebbles, concrete, salt) sold as fertilizer. Michelson et al. (2020) emphasize that fertilizer quality is multi-dimensional and that farmers also consider the appearance of the fertilizer granules as well as the condition of the bag when they evaluate quality.

[9] Detailed experimental instructions for the Tanzania data collection are shown in Online Appendix B. Analogous instructions for the Uganda data collection are shown in Online Appendix C

[10] Ashour et al. (2019) study farmer beliefs about herbicide quality in Uganda and find that farmers believe that 41 percent of herbicide is counterfeit in their local market. Gharib et al. (2020)'s analysis of farmer willingness-to-pay for hybrid maize seed finds that farmers are concerned about fraud and are willing to pay a premium to purchase directly from the seed company.

2.3.1 Focus groups

We held focus groups with farmers in the Morogoro region of Tanzania to establish how they understand the relationship between fertilizer application and crop yields and how they describe and evaluate fertilizer quality. Farmers reported that good-quality fertilizer is beneficial for crop production and crops with fertilizer perform better than crops without fertilizer; its application makes crops grow “fast and strong,” with “high and good yields.” Farmers said that urea fertilizer was the best fertilizer to use; urea would solve the problem of “paddy turning yellow” or “high amounts of salt in the soil.” Farmers reported hearing about the benefits of fertilizer from fellow farmers, extension agents, fertilizer sellers, and fertilizer companies.

Focus groups revealed an important insight about farmer beliefs and fertilizer quality: reports of bad quality fertilizer most often stem from a farmer using fertilizer and getting “bad results” that are inconsistent with what they expect. Farmers tended to describe fertilizer as having binary quality; either the fertilizer is *safi kabisa* (meaning exactly clean/fresh, excellent, very safe) or terrible. Farmers told stories about knowing farmers who had bought what they referred to as “fake fertilizer.” Farmers provided a range of answers with respect to how they evaluate fertilizer quality: the nutrient content of the fertilizer, the fertilizer’s packaging, storage conditions, or the observed physical characteristics. Among those farmers who reported having purchased bad quality fertilizer in the past (36 of our 43 focus group farmers!), half reported that they knew the fertilizer was bad quality because the performance of the crop did not meet their expectations, a third reported it was bad because of the fertilizer’s observed physical characteristics, and the rest reported that it was a combination of these.

2.3.2 Survey data

The Uganda and Tanzania survey data support the finding from the focus groups: farmers believe that much of the fertilizer available to them is poor quality. Before we discuss the particulars of their beliefs, we present summary statistics describing how farmers in Tanzania form their beliefs about fertilizer quality. Table 3 shows summary statistics on how frequently farmers in Tanzania report that a source of information affected their beliefs. Farmers were allowed to report more than one source. In sum, farmers are using multiple sources of information to form beliefs about fertilizer quality. Most farmers say that they form beliefs based on their own opinion, *not* based on their personal results with fertilizer. 21% say they use their own experience to form beliefs, while 22% say they use their observations of others' results. 20% say they use what other farmers have told them about their experiences, and 10% say they use information from the extension agent. Only 1% say they form beliefs based on what they have heard or read in the media.

Table 3: Sources of information in Tanzania

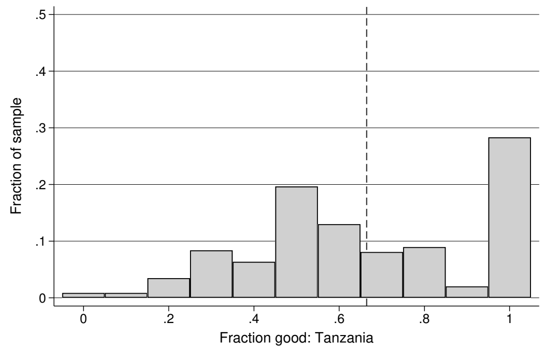
	(1)
	mean/sd
The media	0.01
	(0.12)
My own opinion NOT based on results with fertilizer	0.59
	(0.49)
My own farming results	0.21
	(0.41)
Other results I observed	0.22
	(0.42)
What other farmers told me	0.20
	(0.40)
Extension officers	0.10
	(0.30)
Observations	349

On average farmers in our Tanzanian sample report that they believe 66 percent of the fertilizer in their local market is good quality. Figure 1a shows the distribution of beliefs. Only 28% of farmers believe that all of the fertilizer in their local market is good. Farmers who had previously used fertilizer were more likely to report that more of the fertilizer in their local market was good, while those who had never purchased fertilizer were more likely to say that more fertilizer in their local market was bad.[11] Those who said they used their own results or information from their extension agent to form their beliefs said that more

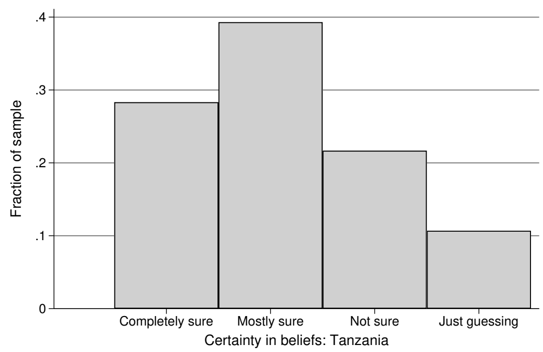
[11] Results not shown, but available on request.

Figure 1: Beliefs about fertilizer quality: Tanzania

(a) Stated belief



(b) Certainty in beliefs



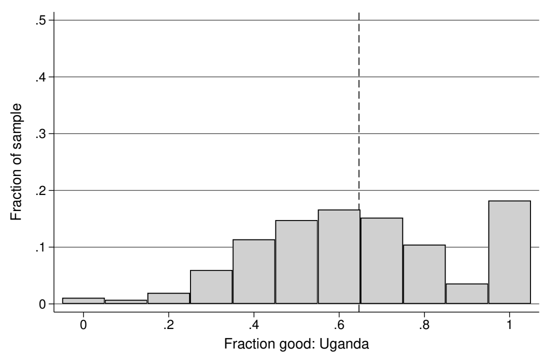
fertilizer in the local market was good, while those who said they formed beliefs based on what others told them thought more local fertilizer was bad.

In Uganda, farmers report on average that they believe 65 percent of the fertilizer in their local market is good quality. Figure 2a shows the distribution of beliefs. Only 18% of surveyed farmers believe that all of the fertilizer in their local market is good quality. As in Tanzania, farmers who had ever used fertilizer were more likely to report that fertilizer in their local market was good. Male farmers, older farmers, and those who owned more land were also more likely to say that local fertilizer was good.

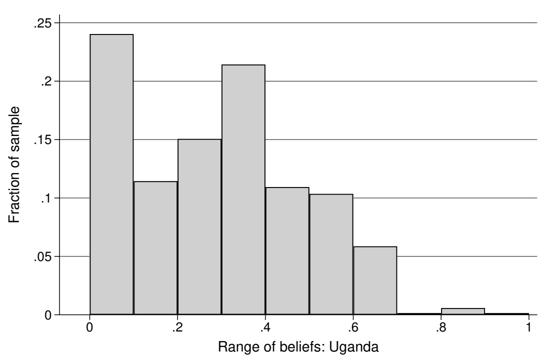
Farmers in both the Uganda and Tanzania data also report being unsure in their beliefs about fertilizer quality in their market. Figure 1b plots a histogram of the responses in Tanzania, where farmers were asked to qualitatively assess their certainty. While 28% reported they were "completely sure' in their beliefs about the rate of good and bad fertilizer, 39% said

Figure 2: Beliefs about fertilizer quality: Uganda

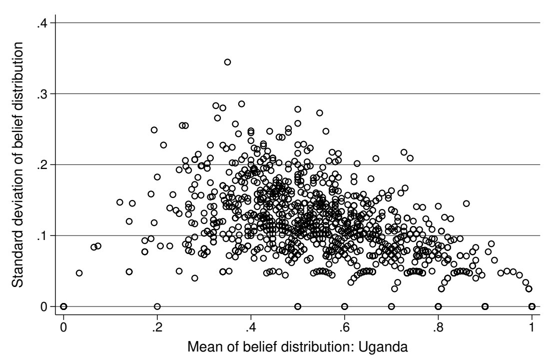
(a) Stated belief



(b) Range of beliefs



(c) Mean and std. dev. of belief distributions



they were “mostly sure,” 22% said they were “not sure,” and 11% said they “had no idea, I’m just guessing.” Male farmers were more likely to say they were completely or mostly sure in their beliefs, as were farmers who had previously used fertilizer. Those who had never purchased fertilizer in their local market were less likely to express certainty in their beliefs. People who said they formed their beliefs based on their own experience, observing others’ experience, talking to others about their experiences, and talking to the extension agent expressed more confidence in their beliefs, while those who said they formed their beliefs just based on their own opinion expressed less certainty in their beliefs.

Figure 2b plots the comparable histogram for the Uganda data, where enumerators elicited the full distribution of farmers’ beliefs about fertilizer quality. While 21% of farmers put all of the stones in the same bin, indicating that the farmer was completely confident in their belief, 79% reported at least some uncertainty. The median farmer distributed stones across four bins. Figure 2c shows a scatter plot of the mean and standard deviation of each farmers belief distribution. While some farmers report perfect certainty in their beliefs across the full range of quality (dots distributed along the x-axis), the data exhibit a wide range of uncertainty for each average belief in the rate of bad fertilizer. Those who had used fertilizer before expressed no more confidence in their beliefs (measured by the standard deviation of the beliefs distribution) than farmers who had not used fertilizer. Male farmers, older farmers, and household heads expressed more confidence in their beliefs, as did those who owned more land.

2.3.3 Willingness-to-Pay experiment

We conducted a binding Becker-Degroot-Marschak (BDM, (Becker, Degroot, and Marschak, 1964)) auction willingness-to-pay experiment with the Tanzanian farmers in our sample.[12] The results of our experiment permit us to test the relationship between farmer willingness-to-pay for fertilizer and beliefs about fertilizer quality. Farmer reported beliefs in the previous subsection about fertilizer quality were not incentivized in either the Tanzania or the

[12] Burchardi, de Quidt, Gulesci, Lerva, and Tripodi (2021) tested four variants of the BDM in rural Uganda and found that comprehension was high and all four yielded similar measures of willingness-to-pay.

Uganda data, raising obvious concerns about reporting bias, incentive compatibility, and experimenter demand effects.

During the BDM auction, enumerators offered farmers a bag of fertilizer purchased in their local market and a bag of fertilizer purchased in Morogoro town (the nearest large market) but that had been tested in a lab and guaranteed to be perfect quality.[13,14] One fertilizer and its corresponding bid was randomly chosen to be the binding round.[15,16]

Results from the BDM auction suggest that our belief elicitation measures concepts are relevant to farmers' willingness-to-pay for fertilizer. Farmers were willing to pay an average of 1151 Tanzanian shillings for the untested fertilizer from their local market and 1686 Tanzanian shillings for tested fertilizer. Table 4 shows the results of an analysis regressing farmer willingness-to-pay on an indicator that the fertilizer was tested.[17] Farmers were willing to pay 46% more for tested fertilizer than for untested. Moreover, our results show that farmer willingness-to-pay for local fertilizer is strongly correlated with beliefs about local quality fertilizer: farmers who believe all fertilizer is good were willing to pay 26% more for local fertilizer than those who believe all fertilizer in the local market is bad. Correspondingly, the premium farmers are willing to pay for tested fertilizer is related to their beliefs about the quality of fertilizer in their local market. Farmers who believe that all fertilizer in their local market is bad are willing to pay a 62% premium for tested fertilizer, while those who believe that all fertilizer in their local market is good are willing to pay only

[13] Farmers were also offered fertilizer from Morogoro town that had not been tested. Farmers believed Morogoro town fertilizer less likely to be counterfeit or adulterated, but still feared that some fertilizer was poor quality. They were willing to pay more for fertilizer from Morogoro town than their local market, but less than for tested fertilizer. We focus on local and tested fertilizer to streamline the presentation.

[14] Fertilizers were offered in a random order, but farmers knew that they would be bidding on more than one type of fertilizer and that only one bid would be binding. Complete experimental instructions can be found in Online Appendix B.

[15] Of those who won the auction, only 2.5% refused to pay the price drawn from the bag.

[16] 75% of farmers reported that the BDM was "easy to understand" and enumerators reported that 71% of farmers "fully understood" the task.

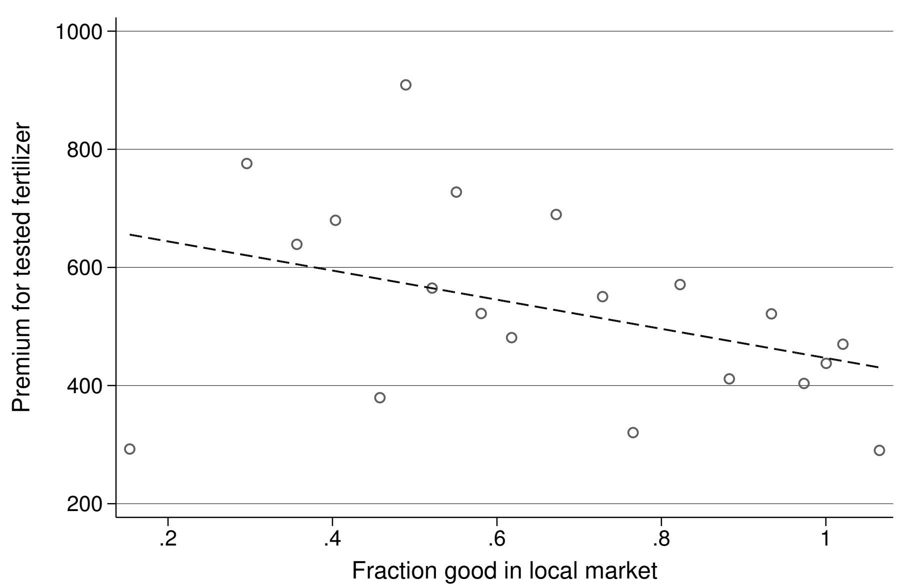
[17] Controls for farmer demographics and farming characteristics were included, including age, gender, whether the farmer was the household head, whether the farmer had completed primary school, household size, whether the farmer had ever purchased fertilizer, whether they had purchased fertilizer in the local market center, the amount of owned land, and whether the farmer recently planted maize and paddy. Controls for whether the respondent completed the beliefs elicitation or willingness-to-pay experiment first, as well as which fertilizer they were offered first, are also included. Standard errors are clustered at the farmer level.

38% more for tested fertilizer. Figure 3 shows this result graphically with a binscatter plot of the premium paid versus beliefs about fertilizer quality in the local market.

Certainty in beliefs is also related to the premium farmers are willing to pay for tested fertilizer. Columns 3 and 4 of Table 4 show results split by whether a farmer said they were "Completely" or "Mostly Sure" of their beliefs (Column 3) or "Not Sure" or "I have no idea, I'm just guessing" about their beliefs (Column 4). The results show that those who are more sure in their beliefs are willing to pay a smaller premium for tested fertilizer, and also that their willingness-to-pay increases with their estimation of the fraction of good fertilizer in their local market. In contrast, those who are less sure in their beliefs are willing to pay a larger premium for tested fertilizer, but the amount they are willing to pay for local fertilizer is not strongly correlated with their beliefs about fertilizer quality.

These results suggest that ambiguity and multiple priors should be included in our learning model. Results from the BDM auction show that farmers who are less certain in their beliefs about fertilizer quality behave differently in their valuation of fertilizer than farmers who are more certain in their beliefs. Those who are less certain about their beliefs are willing to pay less for local fertilizer, even when their best guess is that most fertilizer is good.

Figure 3: Binscatter of premium paid for tested fertilizer by beliefs about fertilizer quality



2.4 Evidence that most fertilizer is high quality

Farmers in multiple studies report suspicions about fertilizer (Sanabria et al., 2013; Bold et al., 2017; Ashour et al., 2019; Michelson et al., 2020). Our results from the BDM suggest that these suspicions affect what farmers are willing to pay for fertilizer of verified quality. The puzzle is that evidence to date suggests that urea fertilizer in the region is good; with nutrient content in compliance with regional manufacturing standards.

Table 5 summarizes results from recent studies of fertilizer quality in East Africa establishing that nutrient quality of fertilizer for sale in the region is good (Sanabria et al., 2013; Mbowa, Luswata, and Bulegeya, 2015; Sanabria et al., 2018a, 2018b; Ashour et al., 2019; Michelson et al., 2020). These are studies characterized by rigorous sampling at multiple levels in the supply chain and large samples. Several of these studies were conducted by the International Fertilizer Development Center (IFDC) - a public international organization focused on international fertilizer quality. Conclusions of the IFDC studies suggest that quality problems are rare, especially in urea. Quality problems may be slightly more common in blended fertilizers. A single study by Bold et al. (2017) finds extremely high average nitrogen deviations of 30% in urea in all 369 sampled bags Uganda. It is not entirely clear why Bold et al. find significant and systemic problems in urea where other studies do not; their results increasingly look like an outlier in the literature.

Table 4: Willingness-to-pay for fertilizer in Tanzania

	(1)	(2)	(3)	(4)
VARIABLES	Baseline	Adding beliefs	More sure about beliefs	Less sure about beliefs
Tested	530.32***	717.47***	681.04***	738.11***
	(42.15)	(121.10)	(152.47)	(200.42)
Fraction good in local market		299.73**	397.62**	47.97
		(147.48)	(195.00)	(243.01)
Tested x Fraction good in local market		-282.09*	-269.04	-216.94
		(160.06)	(197.54)	(277.81)
Constant	1,007.94***	822.29***	623.11*	1,219.36**
	(249.70)	(276.97)	(320.02)	(615.12)
Observations	691	691	468	223
R-squared	0.12	0.13	0.13	0.16

Table 5: Previous studies of fertilizer quality in East Africa

Year sample collected	Country	Acquired from	Authors/study	N	Percent of samples out of compliance
2014	Uganda	Retail sellers	Ashour et al. (2019)	137	0.7%
2014	Uganda	Retail sellers	Bold et al. 2017	369	100%
2010	Ghana	Retail sellers, gov depots	IFDC	222	9%
2010	Nigeria	Retail sellers, gov depots	IFDC	147	All in compliance
2010	Cote dIvoire	Retail sellers, gov depots	IFDC	42	All in compliance
2010	Senegal	Retail sellers, gov depots	IFDC	64	All in compliance
2010	Togo	Retail sellers, gov depots	IFDC	59	All in compliance
2016	Kenya	Retail sellers	IFDC	31	All in compliance
2017	Uganda	Retail sellers	IFDC	38	All in compliance
2015-2016	Tanzania	Retail sellers	Michelson et al. (2020)	300	0.67%
2016	Tanzania	Farmers	Michelson et al. (2020)	121	5%
2019	Tanzania	Retail sellers	Michelson et al. (2020)	45	All in compliance
2018	Tanzania	Warehouses	Michelson et al. (2020)	8	All in compliance
2018	Tanzania	Ships at the port in Dar es Salaam	Michelson et al. (2020)	11	All in compliance

3 Models

We have documented that farmers in Uganda and Tanzania believe that much of the fertilizer available in their local markets is bad, but nearly all of the lab tests of fertilizer quality in the region reveal that fertilizer is very high quality. Moreover, urea fertilizer's uniform texture and color makes it difficult to profitably adulterate and manufacturing errors are uncommon in urea production. Urea is good and is unlikely to be compromised. Farmers should be learning this fact over time. Why, then, do these incorrect beliefs persist in equilibrium? Further, farmers express uncertainty in their beliefs in both settings. Why are farmers not able to purge the ambiguity from their beliefs?

Fertilizer is not the only good for which incorrect beliefs about substandard quality or efficacy maintain over time. Subsistence farmers often have incorrect and uncertain beliefs about other agricultural inputs (Ashour et al., 2019), and families in rural areas often report mistrust of locally available pharmaceuticals and vaccines (Adhvaryu, 2014; Björkman-Nyqvist, Svensson, and Yanagizawa-Drott, 2020; Archibong and Annan, 2021). The phenomenon of incorrect beliefs with regard to a product's quality is not restricted to low-income countries. In the United States, many people hold incorrect beliefs about the rate and severity of childhood vaccine injuries (Dudley, Limaye, Salmon, Omer, OLeary, Ellingson, Spina, Brewer, Bednarczyk, Malik, et al., 2021). As we are writing in early 2021, many people are hesitant to receive the new COVID vaccine because they fear side effects and are additionally unsure of the rate of potential harm. Others have adhered to stay-at-home protocols long after government orders were lifted, even though their anticipated risk of serious harm from COVID is low; they worry about long lasting health problems that may or may not be triggered by COVID, again with unknown probability.

We develop a Bayesian learning model that incorporates two features that together explain both how incorrect beliefs can persist in equilibrium even after many trials and how ambiguity in beliefs can also remain. We apply the model to our fertilizer puzzle example, but it is relevant to other goods and circumstances.

We first assume that farmers form beliefs over the likelihood a product sample is high quality, and that sample quality is binary: all good or all bad. This assumption fits the qualitative evidence from the focus groups in Tanzania that farmers are much more concerned with counterfeiting than adulteration, and adulteration can lead to an obviously all bad bag if the adulterant is something like salt, with pernicious agronomic effects. Next, we add the first main model feature: farmers observe outcomes that are related to the quality of the product sample, but this is through a stochastic process, making quality inference difficult. When a crop yield is low, farmers don't know if they purchased good fertilizer but just happened to experience a bad year, or if they purchased bad fertilizer in a normal year. Finally, we add the second main model feature: we allow farmers to be uncertain in their beliefs and operationalize this assumption by them having multiple priors.

3.1 Misattribution

Misattribution occurs when an agent incorrectly infers that a good quality product sample is bad. Misattribution can happen for many reasons. If there is sufficient stochasticity in the function that determines outputs from inputs, agents will have difficulty determining whether they had bad luck or purchased a bad input. With fertilizer, this occurs because the agricultural production function is noisy. With flu shots, misattribution can happen when a year's vaccine formulation is an imperfect match for the year's circulating viruses. The problem is compounded if agents don't know the parameters of the function perfectly or if their idea of the function is misspecified. For example, nitrogen fertilizer is more effective in certain soil types than others, but farmers are under-informed about the soil type of their plots (Harou, Whitney, Kung'u, and Luedeling, 2021). A farmer may believe that nitrogen fertilizer is equally effective in all soil types. If after using it on their own plots they observe a low yield, they may attribute it to bad fertilizer rather than an inappropriate match between fertilizer type and soil type. For a non-fertilizer example, parents may not know that the characteristics of autism spectrum disorder (ASD) developmentally emerge around the first birthday, just when children usually receive their first measles, mumps, and rubella (MMR) shot. If their child develops indicators of ASD, they may attribute the ASD to the shot rather than developmental regularities.

Four previous papers have modelled misattribution and its effect on learning in contexts like ours. The first two, Björkman-Nyqvist et al. (2020) and Adhvaryu (2014), examine how consumers form beliefs about the quality and effectiveness of antimalarial medicine in Sub-Saharan Africa. The first paper finds that biomedical misconceptions about malaria hamper the ability to learn about the quality of antimalarial medicine (Björkman-Nyqvist, Svensson, and Yanagizawa-Drott, 2013). Specifically, some people believe that malaria can be transmitted by person-to-person contact, when in fact it is transmitted through mosquitoes. Many people also tend to believe that all febrile illnesses are due to malaria, when in fact many are due to non-malaria pathogens. This makes it difficult to infer the quality of anti-malarial drugs, because people believe that reinfection is more common than it is and believe they have malaria more often than they do. They show that beliefs about drug quality are more incorrect in areas where people have more biomedical misconceptions. In a similar vein, Adhvaryu (2014) shows that in areas where malaria is more often misdiagnosed, social learning is inhibited and people are less likely to buy anti-malarials as prescribed. When people are prescribed anti-malarials for non-malarial illnesses, they are substantially less likely to experience reduced symptoms, and they and their social contacts are less likely to believe that anti-malarials cure malaria.

In the agricultural sphere, Hanna, Mullainathan, and Schwartzstein (2014) show that Indonesian seaweed farmers consistently misunderstand the production function by underestimating the effect of pod size on output, and once they are informed about the relationship between output and pod size, they update their understanding of the production function and their input choice in the process. Most relevant to our current work, Bold et al. (2017) examines fertilizer quality and beliefs about quality in Uganda. They develop a Bayesian learning model in which farmers form beliefs about the amount of nitrogen the fertilizer contains and they show that stochasticity in the agricultural production function makes it difficult for farmers to learn about compromised quality of fertilizer in their local area. They are trying to explain why bad fertilizer can persist in a market. Their model predicts that when fertilizer is nearly or perfect quality, as is consistent with the preponderance of evidence regarding fertilizer quality in the region, beliefs about fertilizer quality should converge to the truth within one growing season.

3.2 Multiple priors

Farmers in our surveys have expressed uncertainty about their beliefs, qualitatively in the Tanzania survey and quantitatively in the Uganda survey. We use multiple priors to incorporate this stylized fact into our Bayesian learning model.

It is important to make two distinctions in terminology. First, the difference between risk and ambiguity: risk occurs when an agent doesn't know the outcome of a choice, but they do know the likelihood of the possible outcomes; ambiguity occurs when the agent doesn't know the outcome of a choice, and they are additionally uncertain about the likelihood of various outcomes (Knight, 1921; Ellsberg, 1961). Ambiguity is closely related to multiple priors. A truly ambiguous choice is one in which the agent has no specific ideas of the likelihood of possible outcomes, but this is intractable to model. To operationalize the idea of ambiguity theorists introduced the idea of multiple priors (Gilboa and Schmeidler, 1989), or the idea that rather than holding one fixed idea of the likelihood of an outcome (e.g. the chance of a coin flip landing on heads is 50%, creating a risky situation) agents instead keep several specific likelihoods in mind (e.g. if I get COVID the chance I have long-lasting side effects could be as low as 2% but could be as high as 20%, creating a quasi-ambiguous situation). Second, we must understand the relationship between beliefs and preferences. It is possible for two agents to hold the same multiple prior beliefs but make different choices because one agent is ambiguity averse while the other is ambiguity neutral or even ambiguity loving. Analogously, two agents could have the same ambiguity preferences but make different choices because one has optimistic or narrow beliefs while the other holds pessimistic or wide beliefs. In this study we focus on beliefs and their evolution. Next, we'll review models of learning with multiple priors, focusing on beliefs. We must also make the argument that the existence of multiple priors and range of beliefs matter to decision-making. Unfortunately, the literature directly connecting multiple prior beliefs to decision-making is thin.[18] Rather, previous work focuses on whether models that include

[18] Several authors have studied how single prior beliefs affect agricultural decision-making, including Hill

multiple priors better explains observational data, mostly in finance. Though not directly connected to beliefs, other work tests whether ambiguity averse agents make different choices than ambiguity neutral or loving agents. This literature indirectly shows that beliefs about uncertainty matter to decision-making.

3.2.1 Multiple priors in finance and macro

Epstein and Schneider (2010) review several models of beliefs and ambiguity aversion and their consequences for models of finance. They show how various models predict that agents demand ambiguity premiums in addition to risk premiums, and suggest that this helps resolve several puzzles in finance including the equity premium puzzle, the uncovered interest rate parity puzzle, and selective participation. Ilut (2012) shows that ambiguity aversion explains why the uncovered interest rate parity condition fails to hold because rather than act upon the average signal precision, agents act as if their worst-case prediction will hold. Ilut and Schneider (2014) develop a model of the New Keynesian business cycle that includes ambiguity aversion and show that the dispersion of survey forecasts about growth, analogous to the spread of multiple priors, explain nearly 50% of business cycle frequency movements in the major macro aggregates. Jeong, Kim, and Park (2015) develop an asset pricing model that incorporates intertemporal substitution preferences, risk preferences, and ambiguity preferences, and show that ambiguity can explain up to 45% of the average equity premium in the US stock market from 1960-2006.

3.2.2 Multiple priors in agricultural technology adoption

Several teams of authors have documented the relationship between ambiguity aversion affects technology adoption in agriculture. Engle-Warnick et al. (2011) find that ambiguity aversion reduces the likelihood that Peruvian farmers diversify into potentially high but uncertain return crops. Barham et al. (2014) study grain farmers in the Midwest of the

(2009), Dillon (2016), Giné, Townsend, and Vickery (2017), and Maertens (2017). Attanasio (2009), Delavande, Giné, and McKenzie (2011), and Delavande (2014) review the literature on beliefs elicitation in the developing world.

United States and find that ambiguity averse farmers increase their adoption of uncertainty reducing genetically modified corn. Crentsil, Gschwandtner, and Wahhaj (2020) study the adoption of three new technologies offered to aquafarmers in Ghana and find that ambiguity averse farmers are slower to adopt the technology that entails large fixed costs. Ambiguity averse farmers are also less likely to take up partial insurance contracts. Elabed and Carter (2015) show that 60% of cotton farmers in Southern Mali are ambiguity averse, and that this aversion reduces demand for rainfall insurance contracts by almost half. Bryan (2019) finds that increased ambiguity aversion decreases the adoption of rainfall insurance in Malawi, while ambiguity averse farmers in Kenya do not increase their adoption of new farming technologies when offered limited liability credit while ambiguity neutral farmers do. Belissa, Lensink, and Van Asseldonk (2020) show that while increased risk aversion increases take up of index-based insurance in Ethiopia, ambiguity aversion decreases uptake due to basis risk.

3.2.3 Learning with multiple priors

We build on the Epstein and Schneider (2007) model of learning under ambiguity. They assume that agents hold multiple priors. When exposed to a new data point agents test which priors meet a likelihood criterion. Those that do not are discarded, while the remaining active priors are updated with the new data using on Bayes' theorem. Notably, their model predicts that agents' beliefs will eventually converge to the truth when exposed to enough data. Marinacci (2002) provides a precursor to the Epstein and Schneider model that comes to the same conclusion: with enough data, beliefs should converge to a single posterior that matches the truth. Zimper and Ma (2017) offer an evolution of the Epstein and Schneider (2007) model: rather than discarding priors that do not meet a likelihood criterion, they discard only the priors that do not meet a *log*-likelihood criterion. They interpret this distinction as the decision-maker being more "hard-headed" and less willing to give up perspectives they had been entertaining. They demonstrate that for sufficiently stubborn people, ambiguous beliefs will not converge to a single prior that matches the truth, even with a substantial amount of data. Kala (2019) also presents a robust learning model applied to planting decisions in

India, where farmers must predict the timing of the onset of monsoon. Farmers initially know the distribution from which the optimal planting time is drawn, but that distribution evolves with a random walk due to climate change, which causes uncertainty about model specification. We instead model a time-invariant parameter because most studies of fertilizer quality in this area find perfect or nearly perfect fertilizer quality.

3.3 Our model

We develop a Bayesian learning model in which farmers believe that fertilizer quality is binary ("good" or "bad") and form beliefs over the fraction of fertilizer in their local market that is good. Stochastic noise in yields can lead a farmer to misattribute a poor shock to bad fertilizer. Farmers are unsure in their beliefs, and hold multiple priors. Suppose a farmer thinks that fertilizer quality follows a Bernoulli(p) distribution. In period zero, the farmer has a set of active priors $\mathcal{P}^0 = \{\pi^0(\theta_1), \pi^0(\theta_2), \ldots, \pi^0(\theta_k)\}$ about the value of p and a set $\mathcal{D}^0$ of discarded, or inactive, priors. The farmer learns about p by the observing their own yield realizations $\mathbb{Y}^1 = \{y_1^1, y_2^1, \ldots, y_n^1)$.[19] Every yield realization in each period follows a linear growing process with mean μ and stochastic variation following a $N(0, \sigma^2)$ distribution.

If a yield falls above a threshold s_h, the farmer attributes "good fertilizer," or a success, to that yield realization. If a yield falls below a threshold $s_l < s_h$, then there is another factor that is more evidently the cause of the yield, e.g., a drought; in this case the yield provides the farmer with no information about the quality of the fertilizer. A yield in between the two thresholds is the interesting case. The yield isn't poor enough that it is obvious that another factor dominated; thus, for a yield in between the two thresholds there is a probability q_i that the farmer misattributes the yield to "bad fertilizer," or a failure, and a probability $1 - q_i$ that the farmer does not draw any information from the yield.[20] The farmers inferred fertilizer quality for an informative yield y_i^1 is denoted as x_i^1. If there are m informative

[19] Upcoming drafts will discuss the possibility that the farmer might observe more than one data point per period, for example by observing neighbors plots.

[20] The probability q_i is a linear function from 0 to 1 over $[s_l, \frac{s_l+s_h}{2}]$ and a linear function from 1 to 0 over $[\frac{s_l+s_h}{2}, s_h]$.We define q_i using the z-score of a yield. Letting z_l, z_h, and z_i be the z-scores corresponding to s_l, s_h, and y_i, respectively, then $q_i = 1 - \frac{2}{z_h - z_l}|z_i - \frac{z_h+z_l}{2}|$.

yields, given that the farmer thinks that fertilizer quality follows a Bernoulli(p) distribution, the inferred qualities $\mathbb{X}^1 = \{x_1^1,\, x_2^1, \dots,\, x_m^1\}$ follow a Binomial(m, p) distribution.

Given the data $\mathbb{X}^1$, a prior $\pi^0(\theta)$ is updated to $\pi^1(\theta) = \pi^0(\theta|\mathbb{X}^1)$ according to Bayes' theorem:

$$\begin{aligned}\pi^1(\theta) &= \pi^0(\theta \mid \mathbb{X}^1) \\ &= \frac{f(\mathbb{X}^1 \mid \theta)\, \pi^0(\theta)}{f(\mathbb{X}^1)}\end{aligned}$$

where

$$f(\mathbb{X}^1) = \int f(\mathbb{X}^1 \mid \theta)\, \pi^0(\theta) d\theta$$

The denominator is to normalize the updated prior; the updated prior is proportional to $f(\mathbb{X}^1 \mid \theta)\, \pi^0(\theta)$ and can be written as

$$\pi^1(\theta) \propto f(\mathbb{X}^1 \mid \theta)\, \pi^0(\theta)$$

After observing the yield data and inferred number of plots with good-quality fertilizer and plots with bad-quality fertilizer, the farmer must make a judgement: Which of their multiple priors should they update, and which should they discard? Epstein and Schneider (2007) provide an intuitive procedure: For each $\pi^0(\theta_j) \in \mathcal{P}^0$, the farmer calculates the likelihood of observing $\mathbb{X}^1$, $L(\mathbb{X}^1 \mid \pi^0(\theta_j))$. The farmer picks the prior with the highest such likelihood, $\pi^0(\theta^*) \equiv \text{argmax}_{\pi^0(\theta) \in \mathcal{P}^0} L(\mathbb{X}^1 \mid \pi^0(\theta))$, and compares the likelihood of all the others to it. If the ratio of the likelihood of prior to the highest likelihood is below a learning parameter, γ, then that prior is discarded and not updated. The learning parameter γ governs the extent to which the farmer is willing to reevaluate a prior based on new data. Essentially, the farmer updates the priors that pass a likelihood-ratio test with the most likely prior. Thus,

$$\mathcal{P}^1 = \left\{ \pi^1(\theta) \mid \pi^0(\theta) \in \mathcal{P}^0,\ \frac{L(\mathbb{X}^1 \mid \pi^0(\theta))}{L(\mathbb{X}^1 \mid \pi^0(\theta^*))} \geq \gamma \right\} \tag{1}$$

Discarded priors are added to the set of discarded priors $\mathcal{D}^1$. The likelihood-ratio test is also performed on discarded priors; if a discarded prior passes the likelihood-ratio test it gets updated and is added back into the set of active priors. The evolution of the farmers beliefs over time are given by the priors in the set of active priors. A flexible prior is needed to model the farmer's beliefs. The farmer thinks that fertilizer quality is binary, but they know that they do not know the share of good-quality fertilizer in the market. The Beta-Binomial distribution allows for modeling this situation. The random variable of the number of successful trials, call it X, follows a Binomial(m, p) distribution, while the parameter of the Binomial distribution p follows a Beta(α, β) distribution. The farmer attempts to learn about p.

Dropping indices for brevity,

$$X \sim \text{Bin}(m, p), \quad p \sim \text{Beta}(\alpha, \beta)$$

Which means, letting k be the number yields whose fertilizer is inferred to be good quality,

$$P(X = k \mid m, p) = L(p \mid k) = \binom{m}{k} p^k (1-p)^{m-k}$$

And

$$\pi(p \mid \alpha, \beta) = \text{Beta}(\alpha, \beta) = \frac{p^{\alpha-1}(1-p)^{\beta-1}}{\mathrm{B}(\alpha, \beta)}, \quad p \in [0,1], \;\; \mathrm{B}(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

The posterior is proportional to the likelihood of seeing the data multiplied by the prior distribution. Thus, continuing to drop indices, the posterior $\pi(p \mid m, k, \alpha, \beta)$ is given by:

$$\begin{aligned} \pi(p \mid m, k, \alpha, \beta) &\propto L(k \mid m, p)\pi(p \mid \alpha, \beta) \\ &= \binom{m}{k} p^k (1-p)^{m-k} \frac{p^{\alpha-1}(1-p)^{\beta-1}}{\mathrm{B}(\alpha, \beta)} \\ &\propto p^{\alpha+k-1}(1-\alpha)^{\beta+m-k-1} \end{aligned} \tag{2}$$

The updated α parameter is the prior value of the parameter plus the number of yields whose inferred fertilizer quality is good, and the updated β parameter is the prior parameter value plus the number of yields whose inferred fertilizer quality is bad. To perform the likelihood ratio test, we need to know the likelihood of seeing k for given m, α, and β values,

$p(X = k \mid m, \alpha, \beta)$. This is given by:

$$\begin{aligned}
p(X = k \mid m, \alpha, \beta) &= \int_0^1 p(X = k \mid m, p)\pi(p \mid \alpha, \beta)dp \\
&= \int_0^1 \binom{m}{k} p^k (1-p)^{m-k} \frac{p^{\alpha-1}(1-p)^{\beta-1}}{\mathrm{B}(\alpha, \beta)} dp \\
&= \binom{m}{k} \frac{1}{\mathrm{B}(\alpha, \beta)} \int_0^1 p^k (1-p)^{m-k} p^{\alpha-1}(1-p)^{\beta-1} dp \\
&= \binom{m}{k} \frac{1}{\mathrm{B}(\alpha, \beta)} \int_0^1 p^{k+\alpha-1}(1-p)^{m-k+\beta-1} dp \\
&= \binom{m}{k} \frac{\mathrm{B}(\alpha + k, \beta + m - k)}{\mathrm{B}(\alpha, \beta)}
\end{aligned} \tag{3}$$

3.4 Baseline simulations

We simulate the evolution of a farmers beliefs under four conditions: with and without misattribution, and with and without multiple priors. When we run a simulation, the two statistics of interest at the end of the final time period are: what does the farmer believe, and what is the range of the farmer's beliefs? Given that there can be multiple active priors at a given time, we define what a farmer believes as the average of the active priors and the range of the farmers beliefs as the range between the two furthest active priors.

The simulation requires the following assumptions: the number of time periods over which the farmer learns, the number of priors about the rate of good quality fertilizer along with their means and variances, the percentile of the threshold below which a farmer considers a yield uninformative about fertilizer quality, the percentile of the threshold above which a farmer considers a yield indicative of good quality fertilizer, and the learning parameter

For each specification we set the number of periods to 100. When simulating misattribution, the percentile below which a yield is evidently caused by a factor other than bad fertilizer is 0.15 and the percentile above which a yield is denoted a success is .50. When multiple priors are simulated, the first has an expectation of $p = 0.1$, the second an expectation of $p = 0.2$, all the way to the ninth with an expectation of $p = 0.9$; the variance is set to $p(1-p)/10$.[21][22] We set the learning parameter γ to 0.3. Each time we run a simulation, the two statistics of interest vary due to the stochasticity in the model, so we run each simulation 1,000 times and take averages of the range and central beliefs.

Figure 4 shows the results of each of the four simulations, with beliefs shown on the y-axis and the number of time periods on the x-axis. Panel 4a shows that with no misattribution and a single prior, beliefs converge to the truth over time. Panel 4b shows that with misattribution, beliefs do not converge to the truth. This is because negative natural variation in yield is misattributed to bad fertilizer, so beliefs about the rate of good fertilizer converge to the level that explains the amount of naturally occurring poor yields. Panel 4c shows that with no misattribution and multiple priors, beliefs do converge closer to the truth, but much more slowly, and there is some remaining uncertainty for many periods. Panel 4d shows that with both misattribution and multiple priors, beliefs do not converge to the truth and there is considerable uncertainty in beliefs even after 100 periods.

Taken together, the simulations show how a model with both misattribution and multiple priors can explain both the fact that farmers continue to believe that much of the fertilizer in their local market is poor quality when in fact nearly all of it is perfect, and also the fact that farmers report that they are uncertain in their beliefs.

3.5 Additional simulations

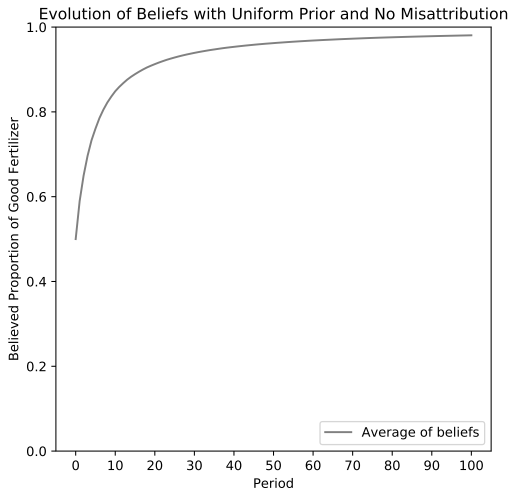
We explore how results of the model simulations vary with different parameter values. Our choices for the yield threshold parameters for the baseline simulations were in part based on the grow out trial data in Bold et al. (2017). Their Figure VII, reproduced below as Figure 5a, shows the distribution of yields using authentic fertilizer (the solid line) is substantially higher than the distribution of yields without using fertilizer (the dashed line). We chose the

[21] We chose to specify the mean and variance of the priors as opposed to their parameters because the mean and variance are more easily interpreted than α and β.

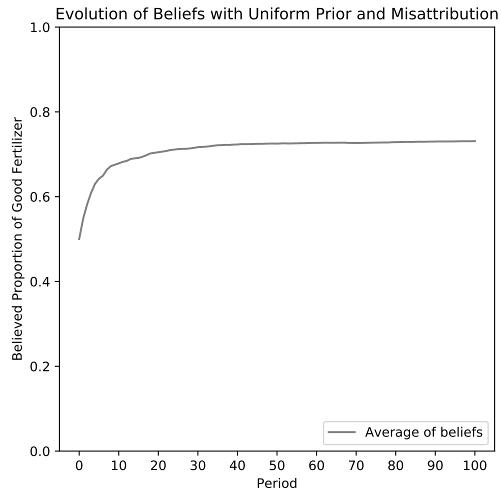
[22] The variance is normalized by 10 to account for the adaptation between the binomial and beta distributions.

Figure 4: Evolution of beliefs with and without misattribution, with and without multiple priors

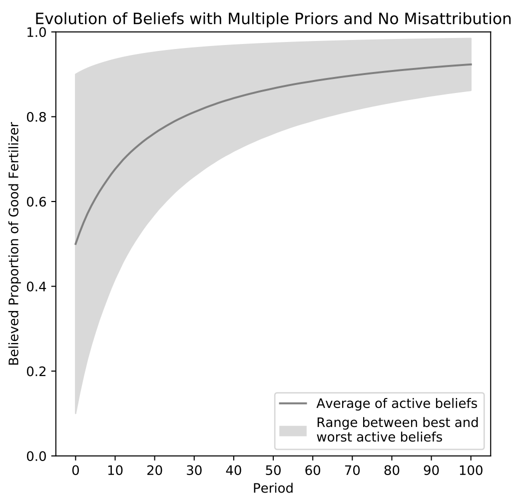
(a) No misattribution and a single prior



(b) Misattribution and a single prior



(c) No misattribution and multiple priors



(d) Misattribution and multiple prior

fiftieth percentile as the upper threshold for which a farmer considers the yield indicative of good quality fertilizer, a "success," and the fifteenth percentile as the lower threshold for which a farmer consider the yield uninformative about fertilizer quality.

However, the Bold et al. (2017) grow out trial data show yields under ideal growing conditions in which fertilizer is applied perfectly to high quality soil. In practice, farmers may not use fertilizer exactly as instructed, and they may have variable soil quality. Figure 5b displays conventional maize yields in our Uganda data for those who did and did not use fertilizer in the first growing season of 2014. Fertilizer use is surely endogenous, so this should not be seen as evidence for or against the efficacy of mineral fertilizer. Instead, this should be thought to represent what a typical farmer might notice if they were observing yields using and not using fertilizer. The plot shows that the yield distribution with fertilizer use is not noticeably higher than the yield distribution without using fertilizer, and the mean yield is actually lower for those who use fertilizer. If a farmer were expecting yield differences the size of those shown in the Bold et al. (2017) grow out trial data, they would be quite underwhelmed by the performance of fertilizer shown in our Uganda data, and may be more likely to misattribute bad yields to bad fertilizer. This suggests that the misattribution problem may be worse than the initially chosen baseline parameters would suggest, and that additional simulations that vary those parameters can be informative.

Figure 5: Yields per acre in Uganda, with and without fertilizer

(a) Bold et al. 2017 grow out trials

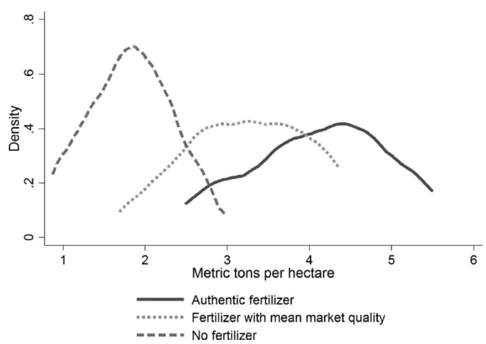


FIGURE VII

Densities of Yield for Different Input Qualities

The density, for each quality combination, is based on 30 randomly assigned plots, with observations from the research managed trials. The solid line depicts the density of yields (metric tons per hectare) when using authentic fertilizer (%N = 46) and farmer seeds. The dotted line depicts the density of yields when using technologies with close to mean market quality (%N = 23) and farmer seeds. The dashed line depicts the density of yields when using the technologies with the lowest quality (%N = 0) and farmer seeds. Data from the experimental plots.

(b) IFPRI survey data

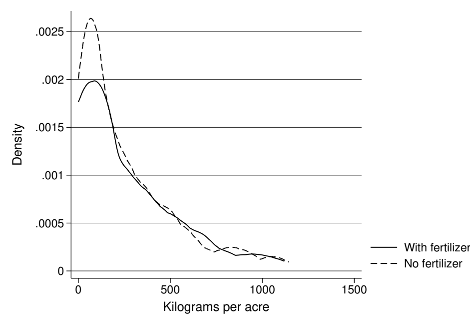
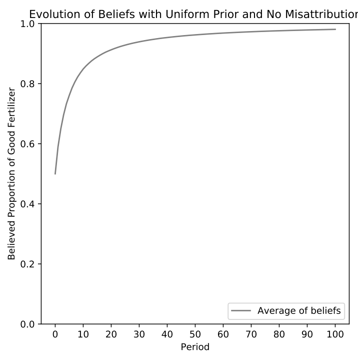


Figure 6 shows simulations for four sets of misattribution parameters. The first column of figures reproduces the simulations with no misattribution. The third column reproduces figures with the baseline misattribution parameters. The second column simulates a situation in which misattribution is not as bad as the baseline scenario (upper threshold 0.5, lower threshold 0.25). The fourth column simulations a situation in which misattribution is worse than the baseline scenario (upper threshold 0.5, lower threshold 0.05). The top row shows simulations with a single prior, while the lower row shows simulations with nine priors. As expected, as misattribution gets worse, equilibrium beliefs are further from the truth. Additionally, the effect of multiple priors is amplified when misattribution is worse; that is, beliefs are not only more incorrect, farmers are less certain of those incorrect beliefs. The misattribution and multiple prior problems compound to reduce willingness-to-pay and use.

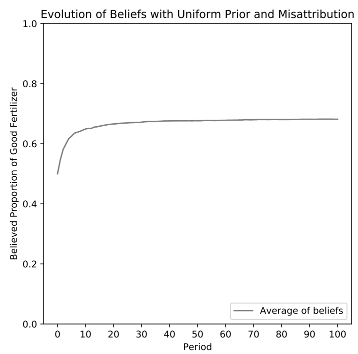
We also simulate the effects of different numbers and ranges of multiple priors. The top row of Figure 7 reproduces the baseline multiple prior simulations with nine multiple priors distributed evenly in the unit interval, using the baseline misattribution parameters. The second row shows simulations of three priors, spread at means of 0.1, 0.5, and 0.9 (wide range). The third row shows simulations of three priors in a narrower range, at 0.3, 0.5, and 0.7 (narrow range). As expected, beliefs in the simulations with three priors converge to a narrower range than the simulations with nine priors.

Figure 6: Varying levels of misattribution

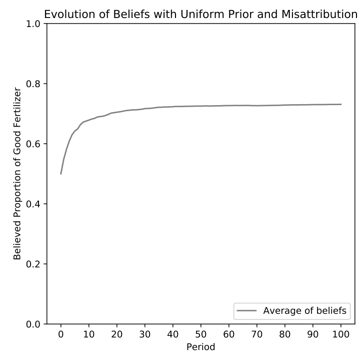
(a) No misattribution and a single prior



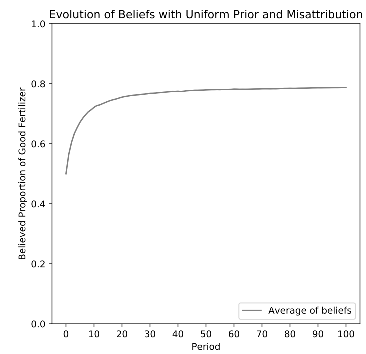
(b) Less misattribution and a single prior



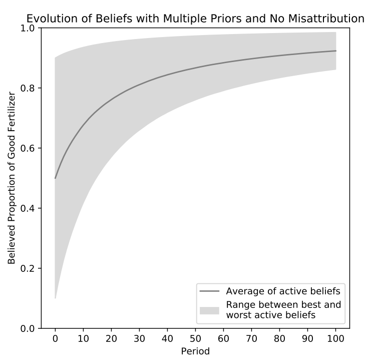
(c) Baseline misattribution and a single prior



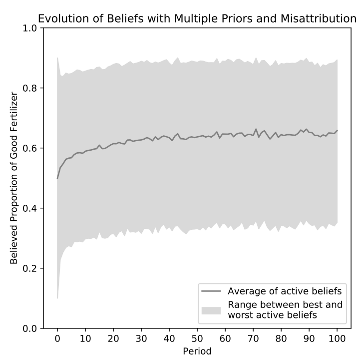
(d) More misattribution and a single prior



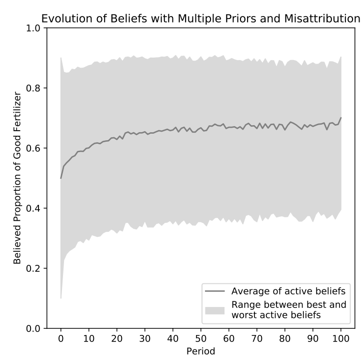
(e) No misattribution and multiple priors



(f) Less misattribution and multiple prior



(g) Baseline misattribution and multiple prior



(h) More misattribution and multiple prior

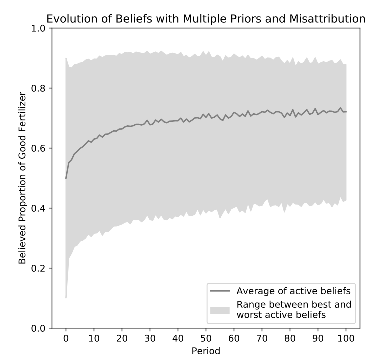
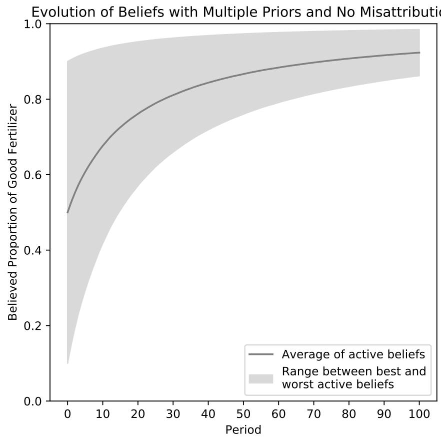
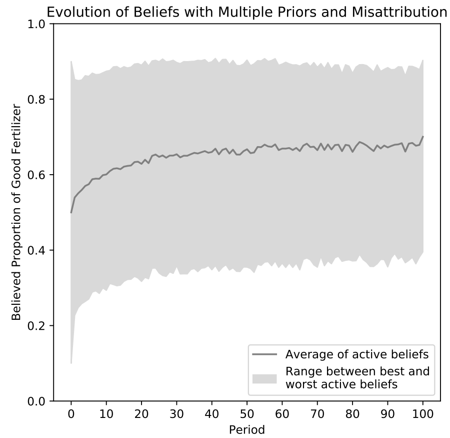


Figure 7: Varying the number and spread of multiple priors

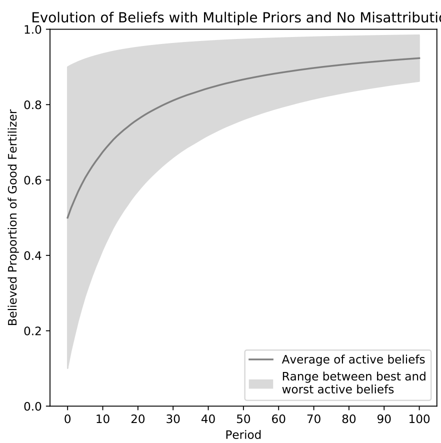
(a) No misattribution and nine multiple priors



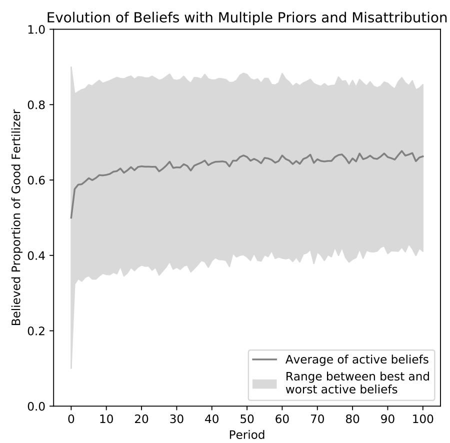
(b) Misattribution and nine multiple priors



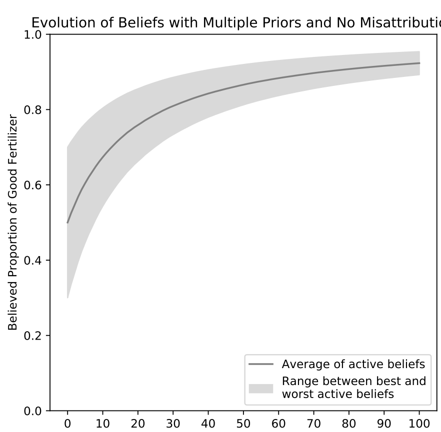
(c) No misattribution and three wide multiple priors



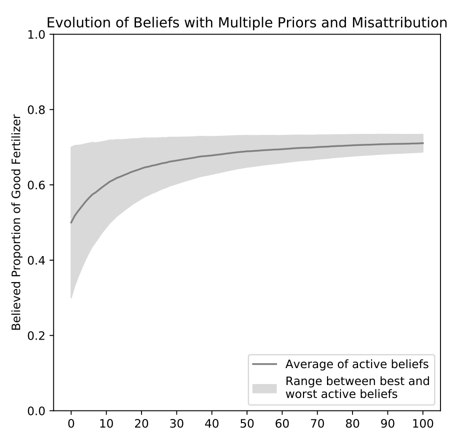
(d) Misattribution and three wide multiple priors



(e) No misattribution and three narrow multiple priors



(f) Misattribution and three narrow multiple priors



3.6 Misattribution, multiple priors, and the weather

Our model illuminates two important insights. First, when farmers misattribute bad yields to bad fertilizer, farmers are unable to learn about the true prevalence of good and bad fertilizer in the market, even when fertilizer in the market is of perfect quality. The second key insight is that when a farmer holds multiple priors, learning is further inhibited, and farmers may be uncertain in their already incorrect beliefs.

The model provides a testable hypothesis that we take to our Uganda data: farmers who live in areas with more variable rainfall will have more incorrect and more uncertain beliefs. More variable rainfall makes it more likely that an individual farmer will experience a negative production shock that they misattribute to bad fertilizer. Analogously, when rains are more variable, farmers are more likely to observe varying experiences with fertilizer, increasing the number and range of opinions about the quality of fertilizer.

We test these ideas empirically using the beliefs data from the Uganda data set and daily precipitation data from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset (Funk, Peterson, Landsfeld, Pedreros, Verdin, Shukla, Husak, Rowland, Harrison, Hoell, and Michaelsen, 2015). CHIRPS data have a 0.05-degree spatial resolution, and include daily precipitation for 5.5 km^2 cells. Precipitation data was gathered for the 10 years prior to the survey in 2014. Precipitation variation was calculated as the variance in daily precipitation during the relevant growing seasons over the 10 years, excluding growing seasons whose total precipitation were two standard deviations below mean growing season precipitation across all farmers and years to account for low-tail events not being misattributed in our model.[23] The study region has two agricultural seasons for maize, the first season "long rains" from February to May and the second season "short rains" from September to November. Primary crops are usually grown in the first season, and fertilizer use is much higher in the first season (10.2% in our data in the first season in 2014) than the second season (5.7% in the second season 2013). We focus on precipitation variation in the first season, but results are robust to including both growing seasons (not shown).

[23]Results are robust to including all daily data points, as well as using a 5th percentile cut off rather than 2 standard deviations. Robustness tables are shown in Online Appendix A.

Table 6 shows the results of analyses regressing farmers mean beliefs, standard deviation of beliefs, and range of beliefs on the historical variance in precipitation in the first growing season, as well as demographic and farming controls.[24] We cluster standard errors at the village level. The estimating equation is shown below. The results show that beliefs are highly correlated with weather variability. On average farmers believe that 62% of fertilizer in their local market is good. Consider the effect of moving a farmer from the 25th percentile of the precipitation variability distribution (variance: 0.215) to the 75th percentile of the precipitation variability distribution (variance: 0.284). These results suggest that that change would reduce the farmer's belief in good fertilizer by 1.79 percentage points, or 2.89%. The coefficient is modest but highly significant (p-value: 0.004), suggesting a relationship between misattribution due to variable rainfall and mean beliefs.

$$Belief_{iv} = \beta_0 + \beta_1 RainfallVariation_{iv} + \beta_2 Demographics_i + \beta_3 Farming_i + \epsilon_{iv} \qquad (4)$$

We also find that rainfall variability is highly correlated with the standard deviation and range of beliefs, suggestive evidence that variable rainfall is also related to multiple priors. On average, the range between a farmers maximum and minimum belief is 0.269. Consider again the effect of moving a farmer from the 25th to the 75th percentile of the rainfall variability distribution. This would increase the range of the farmers beliefs by 0.014, a 5.2% increase.

These results should not be considered causal given the fact that rainfall variability is likely to affect other factors that influence farmer beliefs directly or indirectly, such as fertilizer profitability, market structure, and accessibility. However, results are consistent with the hypothesis that rainfall variability may make misattribution more likely as well as increase the spread of multiple priors, both of which make learning more difficult.

[24] Demographic controls include farmer age, farmer gender, whether the farmer is the household head, whether the farmer has completed at least primary school education, and household size. Farming controls include whether the farmer has ever used inorganic fertilizer and the number of acres owned.

Table 6: Relationship between precipitation variation and beliefs about fertilizer quality: Uganda

VARIABLES	(1) Mean belief	(2) StDev beliefs	(3) Range beliefs
Historic variance in precipitation: First season - Excluding below 2SD	-0.26***	0.07***	0.21***
	(0.09)	(0.02)	(0.07)
Constant	0.62***	0.09***	0.27***
	(0.04)	(0.01)	(0.03)
Observations	1,346	1,346	1,367
R-squared	0.03	0.02	0.02

4 Conclusion

There are many markets in which agents will find it difficult to learn about the quality or effects of a product. In this paper we detail two mechanisms that frustrate learning. When there is noise the process that converts inputs to outputs, an agent may mistakenly attribute a bad outcome to a bad product when in fact the bad outcome was due to natural variation. We call this misattribution. Learning is additionally difficult when the agent is unsure about the likelihood that the product may be good or bad. We operationalize this ambiguity with multiple priors. When present together, our simulations show that beliefs may never converge to the truth and may remain uncertain even after observing many new data points.

We use the example of a farmer forming beliefs about the quality of fertilizer in their local market, and use data from a small willingness-to-pay experiment in Tanzania, a large observational dataset in Uganda, and precipitation data from Uganda to motivate the model and test its implications. We document that farmers in both datasets report significant mistrust of fertilizer quality: 70% of farmers in Tanzania say that at least some of the fertilizer in their local market is counterfeit or adulterated, while 84% of farmers in Uganda have suspicions about quality. They are additionally unsure of their beliefs: 33% of farmers in Tanzania said they were “not sure” or “just guessing” about the rate of bad fertilizer; while the median farmer in Uganda thought that 40% was counterfeit or adulterated, they also said that the rate could be as low as 25% or as high as 55%. Because our beliefs elicitation was not incentivized, we ran a willingness-to-pay experiment in Tanzania to test whether beliefs were correlated with willingness-to-pay for local fertilizer and the premium paid for fertilizer that had been tested in a lab and guaranteed to be perfect quality. We find that farmers who report more optimistic beliefs about fertilizer quality in their local market are willing to pay more for local fertilizer and a smaller premium for tested fertilizer. Additionally, those who report more confidence in their beliefs are willing to pay a smaller premium for tested fertilizer, and that premium varies with their stated beliefs. In contrast, those who report less confidence in their beliefs are willing to pay a larger premium for tested fertilizer, and that premium varies less with their stated beliefs. The model predicts that those who experience lower tail events more often should have worse beliefs because they misattribute more often; they should also have more uncertain beliefs because it is more difficult to dismiss a wider range of multiple priors. We use historic rainfall variability in Uganda to show that farmers who live in regions with greater precipitation variation do have more incorrect and less certain beliefs than farmers who live in regions with more consistent rainfall.

While we apply the model to the example of fertilizer, its elements shed light on how experience goods can become credence goods. Other examples of this include other agricultural inputs such as hybrid seeds and pesticides as well as drugs, vaccines, vitamins, car repairs, and education. It can also apply to environmental policies. For example, suppose a fisherman is told that by adhering to low quotas for a few years, the fish stock will be rebuilt and they will benefit from larger catches in the future. But if there is an environmental shock that interferes with rebuilding, the fisherman may later trust the policy's effectiveness less because they misattributes the poor outcome to a poor policy rather than bad luck.[25] In high-income countries, the quality of credence goods are often certified by scientific bodies and regulatory agencies. In some sense, our results highlight the value of a strong and trusted scientific community and regulatory system, and illustrate what happens when trust breaks down.

[25] We thank Kira Lancker for this suggestion.

For fertilizer and similar products, our work suggests that programs that provide input subsidies or relax credit constraints alone may not encourage long-term use because those programs fundamentally rest on the idea that trying a good a few times will allow the user to identify its benefits. Because of misattribution and multiple priors, fertilizer and other agricultural inputs are not experience goods, so a few uses will not be enough to convince a user of their value. What is needed instead is either a trusted certification program or an education program that significantly reduces misattribution. Our willingness-to-pay experiment was essentially a trial of a certification program: we found that farmers were willing to pay on average 46% more for fertilizer we tested and guaranteed to be high quality than for fertilizer from their local market. One study has experimented with a product assurance program in Uganda that applied scratch labels to input packages to ensure users that the hybrid maize seeds or glyphosate herbicide they were purchasing was indeed the brand on the package (Gilligan and Karachiwalla, 2021);[26] they find that the verification program increased use of the tagged products, shifted beliefs (the treated group reported that they believed the tagged products were of higher quality than non-tagged products), and improved their quality. As a limited regulatory scheme, this program's effectiveness derives from reducing product quality risk from one potential source – product tampering along the retail supply chain. A longer term follow-up in progress has revealed that the treated sample continues to adopt more inputs (particularly tagged inputs) and continue to believe that tagged products are of higher quality, though some uncertainty remains.

While the program in Uganda seems to have had lasting effects, the risk remains that the effectiveness of the program may wane over time. As long as misattribution remains an issue, any certification system will remain vulnerable to a loss of trust. Over the long term, a more sustainable solution could be to inform agents of the stochastic nature of the production function, to convince them that a single bad outcome may be indicative of bad luck rather than a bad input.

[26]The Uganda data for this project are the baseline survey data for this evaluation. Hoel assisted in designing the baseline and endline surveys, but not the analysis of the evaluation data.

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A Additional Tables

Table 7: Understanding of Willingness-to-pay for fertilizer in Tanzania

	(1) WTP First mean/sd	(2) Beliefs First mean/sd	(3) Difference b/se
WTP easy to understand	0.76	0.74	0.02
	(0.43)	(0.44)	(0.05)
WTP a bit difficult to understand	0.23	0.25	-0.01
	(0.42)	(0.43)	(0.05)
WTP very difficult to understand	0.01	0.02	-0.01
	(0.08)	(0.13)	(0.01)
WTP easy to choose	0.63	0.56	0.07
	(0.48)	(0.50)	(0.05)
WTP a bit difficult to choose	0.32	0.40	-0.08
	(0.47)	(0.49)	(0.05)
WTP very difficult to choose	0.04	0.04	0.00
	(0.20)	(0.19)	(0.02)
Enumerator: Farmer fully understood	0.78	0.65	0.12*
	(0.42)	(0.48)	(0.05)
Enumerator: Farmer mostly understood	0.22	0.34	-0.12*
	(0.42)	(0.48)	(0.05)
Enumerator: Farmer did not understand	0.00	0.01	-0.01
	(0.00)	(0.07)	(0.01)
Observations	167	182	349

Table 8: Relationship between precipitation variation and beliefs about fertilizer quality: Uganda - All observations

VARIABLES	(1) Mean belief	(2) StDev beliefs	(3) Range beliefs
Historic variance in precipitation: First season	-0.26***	0.07***	0.21***
	(0.09)	(0.02)	(0.07)
Constant	0.63***	0.09***	0.27***
	(0.04)	(0.01)	(0.03)
Observations	1,346	1,346	1,367
R-squared	0.03	0.02	0.02

Table 9: Relationship between precipitation variation and beliefs about fertilizer quality: Uganda - Excluding seasons below 5th percentile of total seasonal rainfall

VARIABLES	(1) Mean belief	(2) StDev beliefs	(3) Range beliefs
Historic variance in precipitation: First season - Excluding lowest 5%	-0.29***	0.08***	0.24***
	(0.09)	(0.02)	(0.08)
Constant	0.63***	0.09***	0.26***
	(0.04)	(0.01)	(0.03)
Observations	1,346	1,346	1,367
R-squared	0.03	0.02	0.02

B Experimental Details: Tanzania

B.1 Beliefs elicitation

Fertilizers, including urea, have nutrient standards that ensure that the fertilizer will preserve or improve soil fertility and help the crops to grow. For example, the most important element in urea fertilizer is Nitrogen and urea should contain 46% nitrogen. For the purposes of the following questions, good quality means urea fertilizer that has the amount of nitrogen that it is supposed to have: 46% nitrogen. Bad quality means that it has less than 46% nitrogen.

Now, imagine the following scenario FOR YOUR LOCAL MARKET (named above).

For this market, Id like you to imagine that ten farmers from your village would visit agrodealer shops in this market during the long rains season and each purchase 1 kg of fertilizer.

If 10 FARMERS IN YOUR VILLAGE PURCHASE ONE 1 kilogram of fertilizer at (Market from Q43) during the long rains season,

How many would get good quality bags? Record answer below

How many would get bad quality bags? Record answer below

How sure are you that this is the number that would be bad and good? (Enumerator: please read the options out loud.) 1: Completely sure; 2: Mostly sure; 3: Not sure; 4: I have no idea, I'm just guessing.

How did you decide on the numbers you provided us about fertilizer quality in your local market? (multiple answers possible) 1 = the media; 2 = my own opinion/ideas NOT based on results with fertilizer; 3 = my own farming results; 4 = results of other farmers or plots that I observed; 5 = from what other farmers told me; 6 = from extension officers; 7 = other, specify (multiple answers possible)

Now, imagine the same scenario FOR MOROGORO TOWN MARKET.

For MOROGORO TOWN MARKET, Id like you to imagine that ten farmers from your village would visit agrodealer shops in Morogoro Town Market during the long rains season and each purchase 1 kg of fertilizer.

If 10 FARMERS FROM YOUR VILLAGE EACH PURCHASE ONE 1 kilogram bag of fertilizer from agrodealers in Morogoro Town Market during the long rains season,

How many would get good quality bags? Record answer below

How many would get bad quality bags? Record answer below

Have you ever purchased fertilizer in Morogoro Town Market?

How sure are you that this is the number that would be bad and good? (Enumerator: please read the options out loud.) 1: Completely sure; 2: Mostly sure; 3: Not sure; 4: I have no idea, Im just guessing

B.2 Willingness-to-pay experiment

We are doing a market study to see how much farmers like you are willing to pay for different kinds of fertilizer. Today we have three kinds of fertilizer to offer you. You will be able to buy some of this fertilizer if you like.

The first kind of fertilizer is 1 kg of urea fertilizer that we bought in Morogoro town Market in April 2019, and we tested it in a laboratory to make sure it was completely good. It has 46% nitrogen, as is required for good quality by international manufacturing standards.

The next kind is the same as what you probably can buy now in markets. It is 1kg of urea fertilizer that we bought at a market nearby in April 2019.

The last kind is probably familiar to you too. It is 1kg of urea fertilizer that we bought in Morogoro Town Market and in April 2019.

The fertilizer from the market nearby and from Morogoro may also be good. I do not know. It is up to you to think about whether you think the fertilizer is good or not.

Imagine we are in a world where prices are not fixed. The prices you might pay will be determined by chance in the game we are about to do.

You will not have to spend any more money for the fertilizer than you really want to. You may even be able to buy fertilizer for less than you would be willing to pay and less than its price in the market.

You will now have the chance to buy some items from me, but the way we do it here is a bit different from how its done in the market or shop. Lets demonstrate with this soap.

Here is how it works: I will ask you to tell me the maximum price you are willing and able to pay today for the soap. This is called your bid.

After you make your bid, we will play a price game.

In this bag I have many pieces of paper with different prices on them. The prices represent the possible prices for the soap.

I will ask you to pick a piece of paper with a price on it from this bag and we will look at the price together. If the price you pick is less than or equal to your bid, you will buy the soap and you will pay the price you pick from the bag. If the price you pick is greater than your bid, then you cannot buy the soap.

You will only have one chance to buy the soap. You cannot change your bid after you draw a price from the bag. You must state the price that you are actually able to pay now.

We will practice in one moment, but for now, do you have any questions?

SOAP ROUND

Before we do the fertilizer, lets do a version of this bidding with this soap. Well do the same task for fertilizer in a minute, but instead of bidding on the fertilizer, right now we will bid on the soap.

i. What is the maximum amount you are willing to pay for this soap? [Farmer states BID X] BID X:

ii. And if you pick the price [BID X-100 TSH] from the bag in the price game, does that mean you will buy the soap? ENUMERATOR NOTE: Farmer should say YES. If YES: go to (iii) ENUMERATOR NOTE: If farmer says no, read the Instructions again (return to **** on previous page) and then ask question (i) above again.

iii. If you draw the price [BID X+100 TZS], would you want to purchase the soap for [BID X+100]? If YES: go to (iv) If NO: go to (v)

iv. Do you want to change your bid to [BID X+100TSH]? If YES: Ok, your new bid is [BID X+100TSH]. go back to (i) and use BID X+100TSH as the new BID X If NO: go to (v.)

v. So, is BID X truly the most you would want to pay? If YES: go to 53 If NO: go back to I and start over with a new BID.

vi. Now you will play the price game and pick a price from the bag.

If you pick a price that is equal to your BID X or less, you will buy the soap at the price you pick. If you pick a price that is more than your BID X, you will not be able to buy the soap. Are you ready to pick a price?

ENUMERATOR INSTRUCTIONS: Mix the prices in the bag, hold bag above eye level of farmer and have him or her pick a price without looking.

Together look at price that the farmer draws and read the price out loud. [Drawn price is Y]

Record drawn price in question 56. Record if drawn price is higher or lower/equal to the Final Bid in survey in question 57.

vii. Lets look at the price together. a. [If Y<=X]: The price is Y which is [less than/equal to] the amount you said you would be willing to pay for the soap. You can now buy the soap at this price. Exchange payment for soap.

b. [If Y>X]: The price is Y, which is greater than the amount you said you would be willing to spend. You cannot purchase the soap.

viii. Do you have any questions about the task? Next we will be bidding for fertilizer.

Address any questions or concerns the farmer has. Make sure he or she understands the rules. Record answers to survey questions 58-61.

FERTILIZER ROUND

Now you will be bidding to buy fertilizer, just as you did with soap.

Today you will bid on the three kinds of fertilizer we described: Lab Tested pure urea from Morogoro Town Market, local urea, and Morogoro Town Market purchased urea.

However, we will only play the price game for one of your three fertilizer bids. We will randomly choose which one.

Here is how: After you provide bids for each of the three fertilizers, and then you will pick a PAPER out of this bag to determine which kind of fertilizer you will play for in the price game.

Look in the bag. Do you see that there is one paper labeled Local urea, one is Morogoro Town Market purchased urea, and one is Lab Tested pure urea from Morogoro Town Market?

Have you thought about how much you are willing to pay for one kilogram each of these three kinds of fertilizer? Are you ready to bid?

Fertilizer bidding: Now you will bid on the first kind of fertilizer

A. Tested pure urea fertilizer from Morogoro Town Market

Now I would like to offer you a chance to buy excellent quality fertilizer. Here is a 1kg bag of fertilizer that our research team brought from Morogoro Town Market in April of this year (2019). We had it tested in a laboratory, and we found that it is contains 46% nitrogen as is required. It is excellent quality fertilizer. You can hold the bag if you like, but you may not open it.

What is the maximum amount you are willing to pay for this fertilizer? [Farmer states BID X] Enumerator Note: If the farmer doesn't want to place a bid, gently try to get them to do it. If the still refuse, note in Question 62a. Ask them why they dont want to play the game and record in 62b.

Now if you play the price game and pick a price from the bag that is less than or equal to your bid X, you will buy the fertilizer at the price you pick.

If you pick a price greater than your bid of X, you will not be able to buy the fertilizer, even if you change your mind and say you are willing to pay the higher price. Same rules as the soap.

You cannot change your bid after you pick a price. Do you understand?

i. Please, tell me, if you pick the [BID X-100 TSH] price, will you be able to buy the fertilizer? ENUMERATOR: Farmer should reply YES. if they reply NO, explain the instructions again and then ask question again.

ii. And if you pick the [BID X+100 TSH] price, will you be able to buy the fertilizer?

ENUMERATOR: Farmer should reply NO.

If they reply yes, read the Instructions again and then ask question again.

iii. So, is your bid X truly the most you would want to pay for this fertilizer? If YES: KEEP GOING If NO: go BACK AND GET A NEW BID (Q62)

B. Local urea fertilizer

Now I would like to offer you a chance to buy local fertilizer. Here is kilogram of urea fertilizer that our research team bought from a market nearby in April of this year (2019). You can hold the bag if you like, but you may not open it.

C. Morogoro Town Market purchased urea

Now I would like to offer you a chance to buy fertilizer from Morogoro Town Market. Here is a 1kg bag of urea fertilizer that our research team bought from Morogoro Town Market in April of this year (2019). You can hold the bag if you like, but you may not open it.

Now that you have given me a bid for each of the three fertilizers, we will have you pick for which of the three fertilizers you will play the price game.

ENUMERATOR INSTRUCTIONS: Have the farmer choose which market will be the fertilizer for which they will pull a price and then possibly purchase.

Now you will play the price game and pick a price from the bag.

If you pick a price that is equal to your BID or less, you will buy the fertilizer at the price you pick. If you pick a price that is more than your BID, you will not be able to buy the fertilizer. Are you ready to pick a price?

ENUMERATOR INSTRUCTIONS: Mix the prices in the bag, hold bag above eye level of farmer and have him or her pick a price without looking.

Together look at price that the farmer draws and read the price out loud to confirm price. Record drawn price in survey in question 81. Record if drawn price is higher or lower/equal to the BID in survey in question 82.

C Experimental Details: Uganda

C.1 Beliefs elicitation

Facilitator, please read this script to the respondent. The script can be repeated 3 times. After repeating it three times, do not repeat it. Tell the respondent to just try their best.

1. I now want to ask you a different type of question. These questions are about your beliefs. We will start with an example.

2. In my village, there are ten farmers who my father knows very well. I dont know for sure what they have planted, but I will give you my beliefs about how many of these ten farmers could be growing groundnuts.

3. My belief of how many of those ten farmers grows groundnuts is 6 farmers. I think that the chance of 6 farmers growing groundnuts is highest. The smallest number of those ten farmers that could be growing groundnuts is 3. I am certain that there will be at least 3 farmers growing groundnuts.

4. The biggest number of farmers I think could be growing groundnuts is 9. I am also certain that there will be at least one farmer not growing groundnuts. This is what I think for these 10 farmers

[point to the tool card 6] 5. Each of these spaces represents the number of farmers that I think could be growing groundnuts in my village out of the ten. There are spaces for 0 farmers, 1 farmer, 2 farmers, up to 10 farmers.

6. I have here 15 buttons. I will now put buttons in the different spaces. Every button represents a chance that it is this number of farmers in my village that could be growing groundnuts. The more buttons in a space, the higher is the chance that this is the number of farmers out of the ten, who grows groundnuts in my village.

7. I said that the smallest number is 3 farmers, so spaces 0, 1, and 2 will be empty because my belief is that there is no chance that less than 3 of the 10 farmers will be growing groundnuts.

I will cover these spaces because there is no chance.

[cover spaces 0, 1, and 2] 8. I also said that the biggest number of farmers growing groundnuts can not be above 9 out of the 10, so space 10 will also not count and I will cover it because there is no chance.

[cover space 10]

9. I will put the most buttons in the space for 6 farmers; I will put 5 buttons. I think that it is the MOST likely that there will be 6 farmers out of the ten growing groundnuts. The chance of 6 farmers is the highest, in my opinion.

[put the buttons]

10. I will put fewer buttons in the space for 7 farmers, because I think it is less likely that 7 farmers are growing groundnuts than 6. I will put 3 buttons.

[put the buttons]

11. I will put 2 buttons in the space for 5 farmers and for 8 farmers because I think that it is less likely that 5 or 8 farmers are growing groundnuts.

[put the buttons]

12. I will put 1 button in the spaces for 3, 4, and 9 farmers. This is because I think it is possible, but not very likely that so few or so many farmers are growing groundnuts. I think the chance that this happens is low.

[put the buttons]

13. So, there is a very small chance that of 3 or 4 out of the 10 farmers is growing groundnuts [point at space 3 and 4] and a very small chance that 9 out of the ten farmers is growing groundnuts [point at space 9].

14. There is a small chance that 5 or 8 farmers out of the ten are growing groundnuts [point at spaces 5 and 8]. There is a good chance that 7 farmers are growing groundnuts [point at space 7], and the chance of 6 farmers out of the ten growing groundnuts I think is the

highest [point at space 6].

15. Is this clear? Now lets do an example of your expectations.

[choose the respondent who seems to be following the best] 16. I will ask [name of respondent] to tell me about what they believe. You might have different beliefs, and that is OK. Everyone can have different ideas about what they think.

17. Imagine 10 farmers in this village who are not part of these households here today. Based on your experience, out of these ten households, how many do you think might be growing groundnuts?

18. Can you also tell me what is the smallest number of households out of the 10 that we interview in this village that is growing groundnuts?

19. And can you also tell me what is the biggest number of households out of the 10 that we interview in this village that is growing groundnuts?

[cover up the spaces that are outside of the smallest biggest range]

20. Can you now put the buttons in the spaces? Put more buttons in the spaces that you think have a higher chance of being true. So if you think there is a low chance that the number for a space is the number of farmers growing groundnuts, put few buttons. If you think there is a high chance of that number of farmers growing groundnuts, put more buttons.

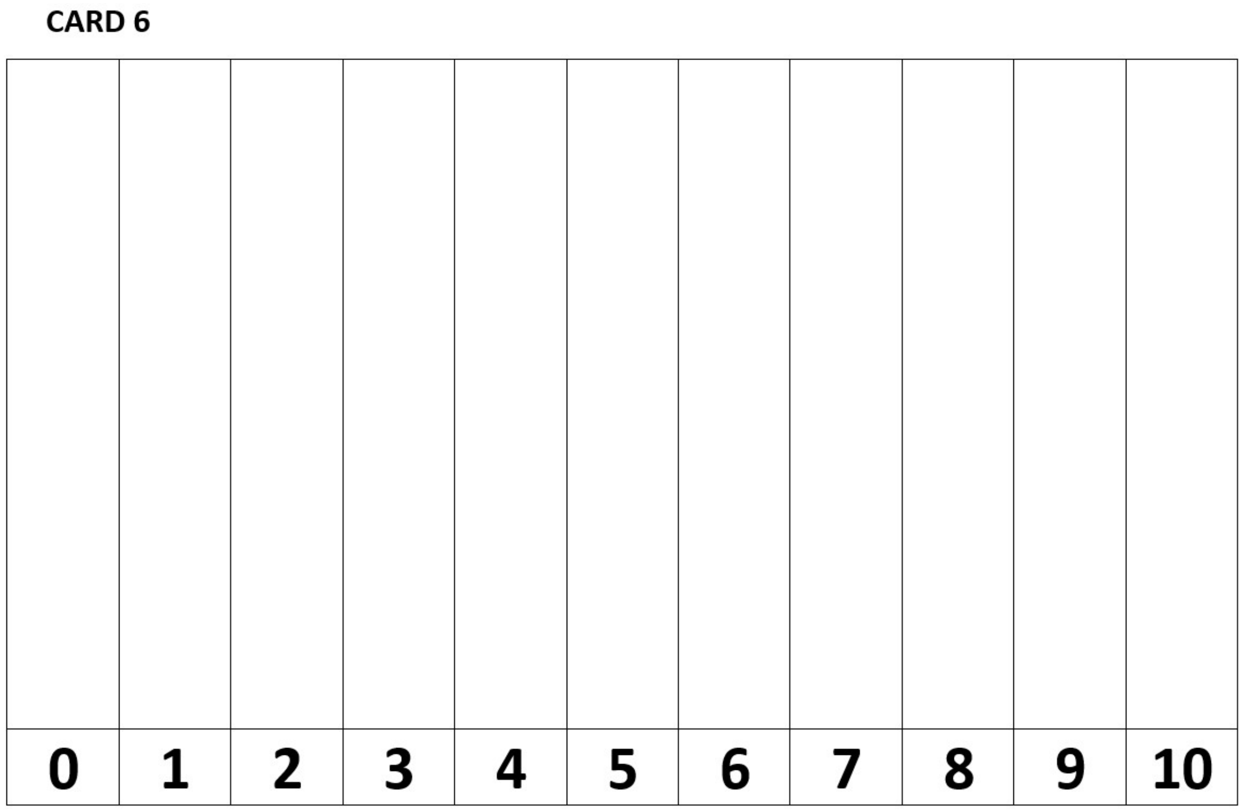
21. You have to use all 15 buttons.

[allow the respondent to place the buttons, and then go through their example]

22. So this means that you are sure that it is not possible for fewer than [minimum] farmers to be growing groundnuts and you are sure that it is not possible for more than [maximum] farmers to be growing groundnuts.

23. You put the most buttons here [point to max buttons] so you think that this number of farmers growing groundnuts has the most chance. You think it is less likely that [point to spaces with fewer buttons] that this many farmers is growing groundnuts. And you think

Figure 8: Belief elicitation card: Uganda



that it is possible but not very likely that this number [point to spaces with the fewest buttons] is growing groundnuts. Is that correct?

24. Now we are going to ask you some questions about your expectations about some agricultural inputs. Sometimes agricultural inputs are not genuine. There are two possibilities: either the product quality is lowered by mixing with fake or inferior product, or, the product quality is lowered by completely replacing it with fake product. Lets take the example of herbicide. Sometimes, people will remove half the contents of the bottle and mix it with water. That is adulteration. Other times, people will remove the entire contents and replace it with water. That is counterfeiting. Have you heard about these practices?

25. Now please go with your enumerator so that they can ask you some questions. Remember, there is no wrong answer.