PEDL Research Papers

This research was partly or entirely supported by funding from the research initiative Private Enterprise Development in Low-Income Countries (PEDL), a Foreign, Commonwealth & Development Office (FCDO) funded programme run by the Centre for Economic Policy Research (CEPR).

Misattribution and uncertainty about beliefs prevent learning

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December 7, 2022

Abstract

We study how incorrect and uncertain beliefs about product quality can persist in equilibrium, using the example of fertilizer in East Africa. Farmers believe much local fertilizer is counterfeit or adulterated, but are uncertain of the rate of bad fertilizer; however, multiple studies find little evidence of poor quality fertilizer. We develop a learning model to explain how these incorrect beliefs persist. We show that when the production process is stochastic, agents misattribute idiosyncratic outcomes to bad inputs. Variable outcomes also interfere with updating, and allow beliefs to remain uncertain. Our learning model and simulations show that learning about quality is not possible when misattribution and multiple priors are present.

JEL Codes: D83, D84, Q12, C91. Word Count: 8708

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1 Introduction

Nearly 40% of Sub-Saharan Africa's population lives in extreme poverty, with the majority of the poor engaged in agriculture - a low-productivity sector characterized by persistently low crop returns. Improving agricultural productivity is central to reducing poverty in the region (Byerlee, De Janvry, and Sadoulet, 2009; Bravo-Ortega and Lederman, 2005) and will require increased use of modern agricultural inputs including fertilizer. The global average nitrogen fertilizer application[1] is 70 kilograms per hectare; farmers in Sub-Saharan Africa average only 15 kilograms per hectare (FAOStat, 2021). A number of explanations for this persistently low fertilizer use have been explored in the literature, including information problems about the technology or its benefits (Foster and Rosenzweig, 2010; Krishnan and Patnam, 2013), heterogeneity in returns (Marenya and Barrett, 2009; Suri, 2011), credit constraints (Carter, Laajaj, and Yang, 2013; 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 they believe the locally available products may be poor quality and have low productivity. Farmers in the Bold et al. (2017) Uganda sample 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, these farmers report that they are not sure about the rate of counter-

[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, Billings, Gilligan, and Karachiwalla, 2015; Michelson, Ellison, Fairbairn, Maertens, and Manyong, 2021). 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. These blends and compounds are often more expensive than urea 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 likely attributable to manufacturing issues rather than adulteration (Sanabria et al., 2013; Michelson, Gourlay, and Wollburg, 2022). We discuss these issues in more detail in Section 2.

[2]Suri and Udry (2022) 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, 2021).

feiting and adulteration. In our Uganda data, the median farmer reported that they thought 40% of fertilizer in their local market was counterfeit or adulterated, but said that the rate could be as low as 25% or as high as 55%. In our Tanzania data, only 28% of farmers said they were "completely sure" about their estimate about the rate of bad fertilizer, while 33% said they were "not sure" or "just guessing." We use a willingness-to-pay experiment in Tanzania to show that farmers who are more pessimistic about fertilizer quality are willing to pay less for local 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.

However, these results present a puzzle because fertilizer in this region 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., 2021; Maertens, Magomba, and Michelson, 2022; Ashour, Billings, Gilligan, Jilani, and Karachiwalla, 2019; Sanabria, Ariga, Fugice, and Mose, 2018a, 2018b).[4] How do incorrect and uncertain beliefs persist in equilibrium?[5]

We develop a learning model that incorporates two features that together explain how incorrect and uncertain beliefs can persist: misattribution and multiple priors. Misattribution occurs when an idiosyncratically bad outcome is attributed to a poor quality input. An agent holds multiple priors when that agent has some sense of the possible likelihoods of various outcomes, but is unsure of the likelihoods of those outcomes. Rather than believe "50% of fertilizer is fake," the agent may think "I'm not sure. It could be that 50% of fertilizer is fake, but it could be as bad as 90 or 100% is fake."[6] We simulate the model and show that

[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 in Bold increasingly looks like an outlier in the literature. Michelson et al. (2022) reviews details on testing protocols, evidence, and possible irregularities. We discuss this point further in Section 2.

[5]We build on Michelson et al. (2021), which first documented the phenomenon of incorrect beliefs about urea quality among farmers in Tanzania. The focus of our paper is why farmers have these beliefs and why they persist. As a part of answering that question, we replicate the willingness-to-pay results from Michelson et al. but using real-stakes binding Becker-Degroot-Marschak (BDM, (Becker, Degroot, and Marschak, 1964)) auctions. Our focus however is understanding why so many farmers believe fertilizer is bad when evidence indicates that urea fertilizer in the region is of reliably good quality.

[6]Multiple priors are one way to represent the concept of ambiguity. Ambiguous beliefs occur when an

when misattribution and multiple priors are present, beliefs do not converge to the truth nor to a single prior, even after 50 periods.

Our results contribute to explaining the persistent problem of low fertilizer use among small farmers: 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).

Our model predicts that farmer beliefs will be more incorrect when outcomes are more variable; more lower tail events are likely to lead to more misattribution. Our model also predicts that beliefs will be more uncertain when outcomes are more variable because it is harder to update priors to a narrow range. We apply these insights to precipitation and farmer beliefs data in Uganda. We find that farmers who live in regions with higher historic variation in precipitation have more incorrect and more uncertain beliefs about fertilizer quality.

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 obstructed by misattribution and multiple priors, fertilizer (and other similar goods) should instead be treated as a credence good – a good whose quality cannot be learned. Beliefs about fertilizer quality must be influenced by something other than use. Other credence goods of this type include agricultural inputs such as seed and herbicides, but also medication, vaccines, vitamins, car repairs, and education.

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

agent does not know the likelihood of various outcomes. Ambiguity 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).

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 fail to function well, one reason why 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 may not on their own 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 may not be enough to convince a user of their value.

The paper begins with a discussion of urea fertilizer in East Africa: its use rates by country and accumulating evidence regarding its good quality. We explain how Tanzanian farmers evaluate fertilizer quality, we present farmers' elicited belief distributions about fertilizer quality, and we show that farmers are willing to pay significantly more for fertilizer of verified nitrogen content. In Section 3 we develop a model of belief updating and learning to explain why farmers persist in believing that urea is bad quality when evidence suggests that it is good. We simulate the model and present results. We then use data from Uganda measuring farmers' beliefs to test an important implication of our model. We conclude with a discussion of the broader implications of our results.

2 Setting and descriptives

2.1 Fertilizer 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 that is 46% nitrogen by weight and among the most common and widely used fertilizers in the world.

According to the Alliance for a Green Revolution in Africa (Kohler, 2020), Uganda used 61 thousand tons of fertilizer in 2016. Urea was the second most widely used fertilizer in the country, accounting for about one sixth of the country's total fertilizer use (about 10 thousand tons). The most used fertilizer by quantity was the NPK blend (17:17:17), which is used in sugar cane cultivation and which accounts for about half of all Uganda's fertilizer use. Urea is the top fertilizer used in Tanzania, accounting for more than 35 percent of the market by volume annually between 2008 and 2016 (Bumb, Ariga, Anand, Cameron, and Nkonya, 2021).

Sheahan and Barrett (2017) document that only 16.9% of small farm households use fertilizer in Tanzania and only 3.2% 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]

Fertilizer is sold by weight and is required to be in accordance with national standards related to nutrient content. For example, urea fertilizer with less than 45% nitrogen is considered out of compliance based on regional regulatory standards in East Africa. Nitrogen can be missing from fertilizer 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 or the material could be something with potentially deleterious effects for current and future production like rock salt. Counterfeiting is an extreme form

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

of adulteration: a counterfeit bag of fertilizer is a bag of completely non-fertilizer material (pebbles, concrete, salt) sold as fertilizer. Michelson et al. (2021) 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. Losses through nitrogen volatilization from open or damaged bags are trivial; Michelson et al. (2021) find no relationship between urea exhibiting caking or visually degraded granules and nitrogen content problems. Manufacturing problems are exceedingly rare in single nutrient fertilizers such as urea. In addition, adulteration and counterfeiting are similarly rare in urea for two reasons. It is a straight fertilizer composed of small prills that are uniform in color and size and is one of the least expensive fertilizers sold in markets, so few substances are plausible adulterants for urea and cheaper than urea.

Previous studies have established that farmers in Sub-Saharan Africa believe there is poor quality urea fertilizer in their local markets. Michelson et al. (2021) find 36% of surveyed farmers (in a sample of 164 farmers) report that urea adulteration is a problem in the market in Morogoro Region, Tanzania. Bold et al. (2017)'s sample of Ugandan farmers believed that urea fertilizer available in their local markets was missing 38% of its nutrients on average.[8] 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.

Table 1 summarizes results from recent studies of fertilizer quality in East Africa establishing that nutrient quality of urea fertilizer for sale in the region is high (Sanabria et al., 2013; Mbowa, Luswata, and Bulegeya, 2015; Sanabria et al., 2018a, 2018b; Ashour et al., 2019; Michelson et al., 2021). These are studies characterized by rigorous sampling at multiple levels in the supply chain and include a large number of fertilizer samples. The table includes Michelson et al. (2021), which conducted sampling in retail shops in the same region as the current study.[9] Several of these studies were conducted by the International Fertilizer De-

[8] Ashour, Gilligan, Hoel, and Karachiwalla (2019) study farmer beliefs about herbicide quality in Uganda and find that farmers believe that 41% of herbicide is counterfeit in their local market. Gharib et al. (2021)'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.

[9] We also purchased and tested 25 50 kilogram bags of fertilizer for this study and had them tested in the

velopment Center (IFDC) - a public international organization focused on fertilizer quality that conducts rigorous assessments using well-documented laboratory techniques. Conclusions of the IFDC studies suggest that quality problems are exceedingly rare, especially in urea. In fact, urea problems are considered so unlikely by IFDC that they rarely sample urea anymore for testing. Sanabria et al. (2018a) write in their Uganda report in 2018, "the reduction of urea sampling, in purpose, is justified by the very rare occurrences of nitrogen shortages in this fertilizer" (p. 8).

A single study - by Bold et al. (2017) - found extremely high average nitrogen deviations of 30% in urea, with nitrogen missing in all 369 sampled bags. No other study approaches the prevalence and magnitude of the Bold et al. (2017) result. Assessments conducted in Uganda over the same time period by Ashour et al. (2019) and Sanabria et al. (2018a) find no evidence problems, despite very similar sampling strategies.[10] Both Ashour et al. (2019) and Bold et al. (2017) sampled from open bags and both sampled widely from retailers.[11] It is not clear why Bold et al. (2017) find significant and systemic problems in urea where other studies do not; their results increasingly look like an outlier in the literature. The Bold et al. (2017) results would imply the presence of significant non-fertilizer fillers in the Ugandan urea; all tested samples from all 129 randomly chosen retailers in two primary maize-growing regions of Uganda exhibit considerable deviations. Sanabria et al. (2018a) comment on the testing results in Bold et al. (2017) and speculate that the issue could be experimental error in the nitrogen testing: "the report does not identify or quantify

United States.

[10]Both Ashour et al. (2019) and Bold et al. (2017) conducted sampling just before the Ugandan government transitioned to providing agricultural extension services through a program called Operation Wealth Creation (OWC), which was launched in June 2014. Extension had previously been provided through the National Agricultural Advisory Services (NAADS). In contrast to NAADS, OWC is managed by the army and is primarily focused on input provision to small farmers. Van Campenhout, Nattembo, and Pauw (2018) discuss OWC timing, implementation, and strategy.

[11]While urea fertilizer is generally sold in sealed 50 and 25 kilogram bags, small farmers tend to purchase fertilizer in one or two kilogram bags. These small quantities are scooped from an open bag at the time of the transaction by agri-dealers or sold in repacked plastic bags prepared by agri-dealers in advance of the transaction. Accordingly, the focus in the literature has been on testing fertilizer scooped from open bags. Michelson et al. (2021) purchase and test primarily one and two kilogram quantities of fertilizer: 88% of their 300 urea samples are small quantity purchases from open bags and all 225 fertilizer sellers in their census sold from open bags. Ashour et al. (2019) also prioritized sampling from open bags in their assessment of fertilizer quality in Uganda. Neither study finds an evidence of quality deterioration associated with samples taken from open bags.

the presence of materials that may be used to dilute nitrogen content in the urea samples. Dilution is the only possible way of reducing nitrogen content in urea. The nitrogen content in the samples used as evidence could be below 46% as a result of deficiencies in the use of the Kjeldahl method [the one used in Bold et al. (2017)], especially when the method is applied manually and by personnel with limited experience analyzing fertilizers. A very common mistake is assuming that a lab with experience analyzing soils will perform well analyzing fertilizers." Bold et al. (2017) do not provide evidence of the presence of fillers, nor do they provide an estimate of the analytical error in their measures.

Of course fertilizer quality is not merely related to the nitrogen content. Michelson et al. (2021) show that fertilizer's observable characteristics are also important to farmers purchasing decisions and are often degraded: powered granules, caking and discoloration are common. While Michelson et al. (2021) show that these attributes do not relate to measured nitrogen, they can complicate application. Farmers report that they break up clumped fertilizer before application, for example. The observed degradation in physical attributes is not found on average to be sufficient to affect yield impacts. 41% of the 300 agri-dealer urea samples in Michelson et al. (2021) exhibited one or two small clumps. It could be that farmers are making assessments about quality based on average observable characteristics, further misattributing bad agronomic quality to bad observable characteristics.

2.2 How Tanzanian farmers assess fertilizer quality

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, how and where they purchase fertilizer, and how they describe and evaluate urea fertilizer quality. We also interviewed stakeholders in the fertilizer industry about the prevalence of bad quality fertilizer.[12] Farmers reported that good-quality fertilizer is beneficial for crop production and that crops with fertilizer perform better than crops without fertilizer; its application makes

[12]We interviewed the director of regulatory services for the Tanzania Fertilizer Regulatory Authority, a senior agronomist at YARA Tanzania Limited, one of Tanzania's largest fertilizer companies, a project manager at the African Fertilizer and Agribusiness Partnership, and an agricultural reporter at Tanzania's major English-language newspaper, The Citizen.

Table 1: 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%
2013-2014	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. (2021)	300	0.67%
2016	Tanzania	Farmers	Michelson et al. (2021)	121	5%
2019	Tanzania	Retail sellers	Michelson et al. (2021)	45	All in compliance
2018	Tanzania	Warehouses	Michelson et al. (2021)	8	All in compliance
2018	Tanzania	Ships at the port in Dar es Salaam	Michelson et al. (2021)	11	All in compliance
2019	Tanzania	Retail sellers	this study	25	All in compliance

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"– yields 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 or 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.

The director of regulatory services at the Tanzanian Fertilizer Regulatory Authority (TFRA) shared a typical case: tobacco farmers in Tanzania's southwest had complained to TFRA in 2018 that the fertilizer they had purchased and used had been poor quality. Their rationale? There was no change in height of their plants 2-3 weeks after applying fertilizer, which was inconsistent with their experience applying fertilizer in the past. The TFRA director travelled to the southwest region to meet with the farmers, tested the fertilizer, and found that it was good quality, with the correct amount of nutrients.[13] A report from the Inter-

[13]The field director coordinating our focus groups and interviews shared with us another relevant example. Two farmers with fields across the road from each other applied urea to their maize, but the crops in on one field performed significantly better than the other. Once crop was shorter and a bit yellow in the leaves. The farmers complained to the field director that the fertilizer that the farmer applied on the field that performed poorly was bad quality and causing this difference. It turns out the farmer with the good crop performance had applied urea fertilizer that included sulfur (ammonium sulfate fertilizer) as well as nitrogen. The farmers had not been aware or had forgotten that they had applied the fertilizer with sulfur. The two fertilizers are branded similarly and cost about the same. The addition of the sulfur in an area with widespread sulfur deficiencies in the soil was causing the farmer's crops to perform better. Neither fertilizer was bad quality,

national Fertilizer Development Center in 2018 on fertilizer quality in Uganda documented the phenomenon of farmers commonly attributing crop growth problems to bad fertilizer: "Complaints made by farmers that cannot be directly linked to fertilizer as the sole cause. Crop failure can be attributed to many causes, ranging from poor crop nutrition due to insufficient use of fertilizers to limited or absent crop protection and other crop management problems" (Sanabria et al., 2018a).

2.3 Farmer beliefs about fertilizer quality

Our survey data come from two primary sources. The first we collected with 348 farmers in 18 villages in the Morogoro region of Tanzania in July 2019. The second data set is a representative household survey of the maize growing regions of Uganda and includes 1388 households in 239 villages. These Uganda data were collected by the International Food Policy Research Institute (IFPRI) in July-August 2014 (Ashour et al., 2015).[14,15]

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

The 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 fertilizer. The farmer was then asked how many of these ten bags of fertilizer would be good

but the fertilizer that the farmers identified as bad quality was assessed by the farmers as bad in comparison with the one that was performing better because it was more suitable for the soil (see (Harou, Madajewicz, Michelson, Palm, Amuri, Magomba, Semoka, Tschirhart, and Weil, 2022)).

[14]The Uganda data are a baseline for a multi-year impact evaluation by IFPRI. Details are available in (Ashour et al., 2019) and (Gilligan and Karachiwalla, 2021). Hoel assisted in designing the baseline and endline surveys, but not the analysis of the evaluation data.

[15]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 2: Farmer summary statistics, Uganda and Tanzania samples

	(1) Uganda mean/sd	(2) TZ mean/sd
Acres owned/cultivated	2.57	3.02
	(3.96)	(2.06)
Ever used/bought mineral fertilizer	0.15	0.34
	(0.35)	(0.48)
Used mineral fertilizer year surveyed	0.11	0.12
	(0.31)	(0.32)
Observations	1388	348

Notes: Table shows summary statistics of the number of acres owned or cultivated, whether the respondent had ever used mineral fertilizer, and whether the farmer used fertilizer in the previous year. Ugandan data were collected in 2014; Tanzanian data were collected in 2019.

quality or bad quality (counterfeit or adulterated). Farmers were also asked to report how certain they were in their belief.[16]

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 likelihood of buying bad fertilizer. We focus on one kilogram bags in the elicitation because this is a dominant unit of purchase among small farmers in the region. The practice of purchasing small quantities from open 25 or 50 kilogram bags is widespread and repackaged bags of one or two kilograms were available in nearly all agri-dealer shops visited by the study team. Farmers in the focus groups also discussed purchasing fertilizer in these small quantities.[17]

The Uganda and Tanzania survey data support the finding from the focus groups: farmers believe that much of the fertilizer available to them in local markets is poor quality. Before we discuss the particulars of their beliefs, we present summary statistics in Table 3 describing how farmers in Tanzania form their beliefs about fertilizer quality. Farmers were asked about which information sources affected their beliefs and 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

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

[17]The farmer makes their assessment at the market level rather than with respect to a specific agri-dealer in a particular market. The markets are clusters of small retail shops selling agricultural inputs including seeds and herbicides. However, Michelson et al. (2021) show that only 41% of shops in the region have a license to sell fertilizer and the sector exhibits considerable churn, with vendors entering and going out of business with high frequency. Michelson et al. (2021) also use direct questions to assess farmer concern about the quality of fertilizer that they buy. They find that 24% of farmers report that purchasing high quality fertilizer is among their top concerns at the start of the growing season and that 43% of the farmers they survey believe at least some of the fertilizer for sale in their local market is adulterated. Further, they show that these quality sensitive farmers are attentive to the observable physical characteristics of fertilizer; they are willing to pay significantly less for clumpy or discolored fertilizer though they do revise their WTP in response to information that the fertilizer has been lab tested and found to be agronomically good.

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 about fertilizer in Tanzania

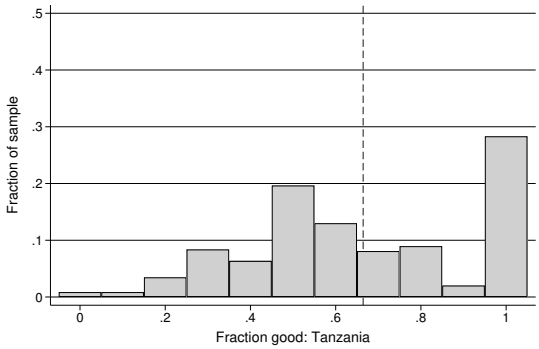
	(1)
	mean/sd
The media	0.01
	(0.12)
My own opinion NOT based on results with fertilizer	0.59
	(0.49)
My own farming results	0.21
	(0.41)
Other results I observed	0.22
	(0.42)
What other farmers told me	0.20
	(0.40)
Extension officers	0.10
	(0.30)
Observations	348

Notes: Table shows summary statistics of farmers in Tanzania reporting from what sources they received information about fertilizer quality.

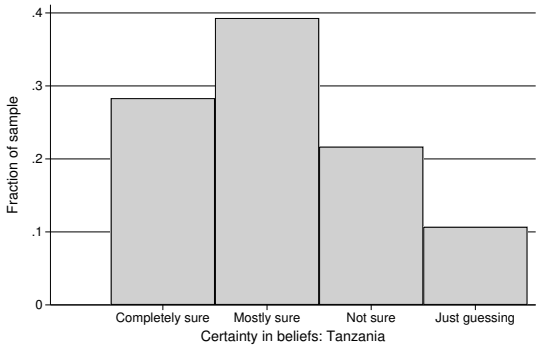
On average, farmers in our Tanzanian sample report that they believe 66% of the fertilizer in their local market is good quality. Figure 1a shows the distribution of beliefs with a vertical dashed line indicating the mean. Only 28% of farmers believe that all of the fertilizer in their local market is 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. Those who said they used their own results or information from their extension agent to form their beliefs said that more 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.

Figure 1: Beliefs about fertilizer quality: Tanzania

(a) Stated belief



(b) Certainty in beliefs

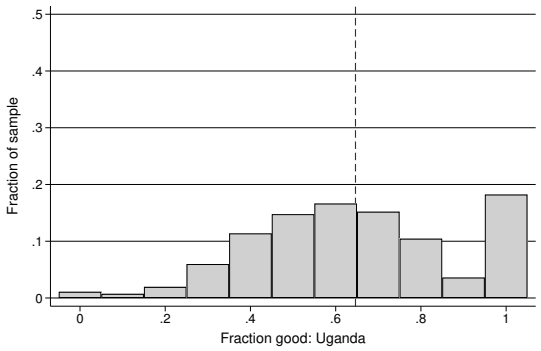


Notes: The first panel of the figure shows a histogram of Tanzanian farmers' stated beliefs about the fraction of fertilizer that is good in their local market. The figure shows that while 28% of farmers believe all of the fertilizer in their local market is good, on average farmers think that only 66% of fertilizer available to them is good. The second panel of the figure shows that while 29% of farmers were completely sure of their estimation of the fraction of fertilizer that is good in their local market, most reported feeling uncertain.

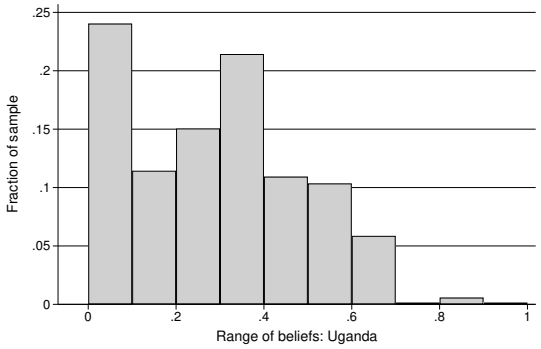
In Uganda, farmers report on average that they believe 65% of the fertilizer in their local market is good quality. Figure 2a shows the distribution of beliefs with a vertical dashed line indicating the mean. Only 18% of surveyed farmers believe that all of the fertilizer in their local market is good 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.

Figure 2: Beliefs about fertilizer quality: Uganda

(a) Stated belief



(b) Range of beliefs



Notes: The first panel of the figure shows a histogram of Ugandan farmers' stated beliefs about the fraction of fertilizer that is good in their local market. The figure shows that while 18% of farmers believe all of the fertilizer in their local market is good, on average farmers think that only 65% of fertilizer available to them is good. The second panel of the figure shows the range of Ugandan farmers' beliefs. When asked their beliefs about the maximum and minimum fraction of good fertilizer in their local market, 21% of farmers reported perfect certainty in their beliefs, while the median farmer reported a range of 40 percentage points.

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, 33% said they were either not sure or just guessing.

Figure 2b plots the comparable histogram for the Uganda data, where enumerators elicited the full distribution of farmers' beliefs about fertilizer quality. 79% reported at least some uncertainty and the median farmer distributed stones across four bins. Those who had used fertilizer before expressed no more confidence in their beliefs 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.

2.4 Farmer willingness to pay for fertilizer

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) that had been tested in a lab and found to be of perfect quality with 46% nitrogen content.[18,19] One fertilizer and its corresponding bid was randomly chosen to be the binding round.[20,21]

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. 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

[18] Farmers were also offered fertilizer from Morogoro town that had not been tested. Farmers believed Morogoro town fertilizer less likely to be bad quality than local fertilizer, 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.

[19] 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 C.

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

[21] 75% of farmers reported that the BDM was "easy to understand" and enumerators reported that 71% of farmers "fully understood" the task.

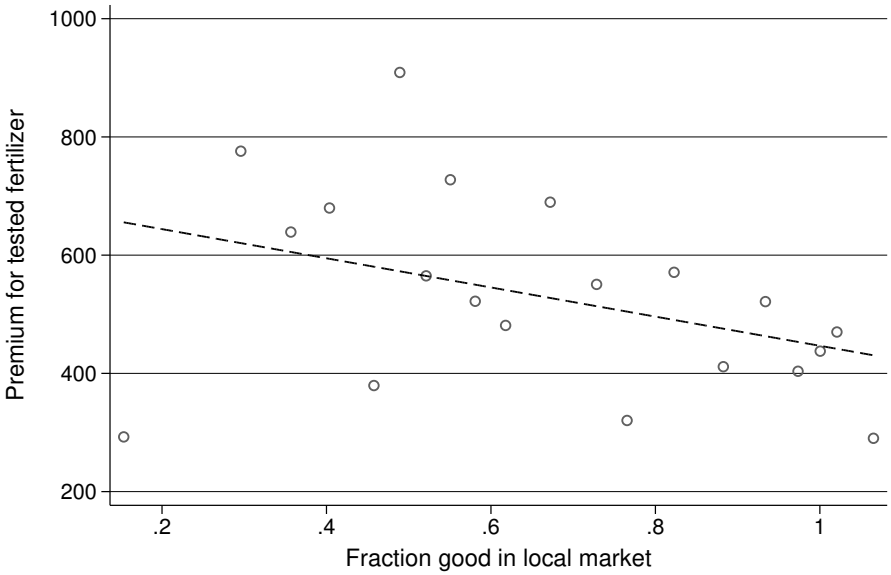
farmers are willing to pay for tested fertilizer is related to their beliefs about the quality of fertilizer in their local market. Farmers who believe that all fertilizer in their local market is bad are willing to pay a 62% premium for tested fertilizer, while those who believe that all fertilizer in their local market is good are willing to pay only 38% more for tested fertilizer. This indicates that farmers who are more uncertain of their beliefs are willing to pay less for fertilizer of unknown quality, which indirectly confirms that they are ambiguity averse. Appendix Table 7 shows the results of the analysis regressing farmer willingness-to-pay on an indicator that the fertilizer was tested.[22] 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 Appendix Table 7 show results split by whether a farmer said they were completely or mostly sure of their beliefs (Column 3) versus not sure of 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 uncertainty about beliefs 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 value fertilizer differently 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.

[22] 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.

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



Notes: Figure shows the regression line and a binscatter plot of the premium farmers in Tanzania are willing to pay for fertilizer that has been tested and assured to be high quality relative to that farmer's beliefs about the fraction of fertilizer that is good in their local market.

3 Learning Model

3.1 Belief Updating Model

We develop a learning model to reconcile three stylized facts: 1) farmers believe much of the fertilizer available to them is low quality, 2) farmers are uncertain about those beliefs; 3) the fertilizer in the local area is in fact mostly good. While other learning models in the literature can explain how facts 1 and 3 can coexist with misspecified models and rational inattention, considerably less attention has been paid to understanding beliefs that remain uncertain after many periods, a key feature of our context.

One reason that existing models in the literature predict beliefs that quickly converge to a narrow (more certain) posterior is because they assume a special form of initial "non-informative" prior: a Beta distribution seeded with $\alpha = \beta = 1$, which is the uniform distribution. When one imagines an agent who initially has no idea of the probability of a given outcome, it is natural to assume that the agent starts with a flat belief distribution spread evenly between 0 and 1. That is in fact what Bayes himself as well as Laplace (who independently discovered Bayes' Theorem) thought of as a reasonable "noninformative prior" for a binomial model (Gelman, Carlin, Stern, Dunson, Vehtari, and Rubin, 2014). However, the Bayesian updating process of a binomial model modeled with a Beta distribution will by definition result in a posterior variance that quickly narrows with repeated observations; this dynamic is clearly not consistent with our setting. We therefore borrow an idea from the microeconomic theory and experimental literatures and introduce the possibility of ambiguity as modeled by multiple priors ((Marinacci, 2002), (Epstein and Schneider, 2007), (Zimper and Ma, 2017)).

We begin with a model of a farmer observing crop yields and attempting to determine whether the fertilizer he used was good or bad. We first introduce misattribution – the idea that the farmer can incorrectly conclude from a poor yield that the fertilizer he used was bad. We discuss how the Bayesian updating of beliefs formed from observing Bernoulli trials is typically modeled with a single prior following the Beta distribution, and show how this

is inconsistent with our data. We then introduce the idea of multiple priors. Specifically, we model the initial "non-informative" prior as an equally weighted average of nine Beta distributions spread evenly across the unit interval, and update each of the multiple priors independently with new each data point. Uncertainty in beliefs is represented by the distance between the highest and lowest priors. Our model and its simulations explore how the three stylized facts can persist over time, and which features of the model are critical to explaining their persistence.

Consider a farmer who observes crop yields after using fertilizer on a single plot over multiple periods.[23] Following qualitative evidence from our focus groups and interviews, we assume the farmer believes fertilizer quality is binary, either good or bad quality, leading to a binomial model.[24] The farmer forms beliefs about the rates of good fertilizer in the local market: in time t these beliefs are denoted as p_t. The farmer also holds beliefs about the distribution of yields the plot will produce if no fertilizer is applied or if bad quality fertilizer is applied,[25] represented by $F(y|b)$, as well as beliefs about the distribution of yields they will observe if they use good quality fertilizer, $F(y|g)$.

We assume that beliefs about yields from good quality and bad quality fertilizer are known and fixed to isolate the effects of misattribution on the farmer's beliefs about the proportion of good quality fertilizer in their market. This is a very strong assumption, and our model should thus be considered as a best case scenario for learning about the rate of good fertilizer in the market. A more complex model could incorporate learning about both yield curves and fertilizer quality, but that is beyond the scope of this paper and warrants further work. The distance between the means of the yield distributions and their relative variances will of course influence how a farmer learns from a given yield observation. In practice farmers may hold correct or incorrect beliefs about these yield distributions, and that will influence their ability to learn about the rate of good fertilizer, as in Heidhues, Kőzegi, and Strack

[23] We abstract away from the possibility of social learning.

[24] This assumption is consistent with existing models that assume costs to holding complex data in mind and that individuals thus simplify their impressions of data points (Ortoleva, 2013).

[25] We assume that applying bad quality fertilizer is equivalent to applying no fertilizer, and that the farmer assumes counterfeit fertilizer is not deleterious. In our survey data from Tanzania, farmers believed plots with no fertilizer and with bad fertilizer would produce 834 and 778 kilograms of dried, shelled maize per hectare, respectively; the difference is not statistically distinguishable.

(2018). We simulate different assumptions about the distance between and shape of these yield distributions to see how they influence learning about the quality of fertilizer.

In each period the farmer uses fertilizer and then observes a yield, y_t, and uses that new information to update their beliefs. The behavior in our model could be micro-founded with a target input model where the farmer's optimal decision to use fertilizer is affected by their beliefs about the returns to good and bad quality fertilizer and the farmer's beliefs about the probability of drawing good quality fertilizer when purchasing fertilizer from the market. Bold et al. (2017) provide an example of such a model. This model would generate a period of fertilizer use - the learning period - and then use would stop if beliefs about the returns to fertilizer converge below a point or continue if beliefs are above that point. We choose not to micro-found the model given the many assumptions required regarding beliefs about input and output prices as well as risk and ambiguity aversion preferences. This is another way in which our model should therefore be considered a best-case scenario for learning - we show what happens to beliefs if the farmer uses fertilizer continuously over time.

Stochastic noise in yields may lead a farmer to misattribute a poor yield draw to bad fertilizer. We assume that for a given yield y_t, the farmer compares the likelihood that the yield was drawn from $F(y|g)$, $L(F(y|g)|y_t)$, to the likelihood the yield was drawn from $F(y|b)$, $L(F(y|b)|y_t)$. The farmer attributes the fertilizer to the quality associated with the higher likelihood.[26] However, if the two likelihoods are too similar to each other, the farmer may decide that the yield is too difficult to interpret and that they cannot therefore infer fertilizer quality from it.[27] This behavior can be thought of as "caution": the farmer may know that the yield distribution when using good fertilizer overlaps with the yield distribution using no or bad fertilizer, and thus may be hesitant to draw a conclusion about fertilizer quality from a yield that could be drawn from either distribution. This attribution process is represented by the following, where g and b are "good" and "bad," respectively, and γ is the threshold above which the farmer considers the relative difference in likelihoods informative:

[26] As likelihoods are not invariant to transformations, it is the relative distance between the likelihoods that drives the process, not the absolute difference.

[27] It is also possible that a farmer could easily know that a poor yield is not due to bad fertilizer, for example because of an obvious drought or pest infestation. We assume that the farmer deems these yields uninformative.

$$x_t = \begin{cases} g, & \frac{L(F(y|g)|y_t)}{L(F(y|b)|y_t)} > \gamma \\ b, & \frac{L(F(y|b)|y_t)}{L(F(y|g)|y_t)} > \gamma \\ \text{uninformative}, & \text{otherwise} \end{cases} \tag{1}$$

The behavior in our model is different from a misspecified learning model (Esponda and Pouzo, 2021), a rational inattention model (Gabaix, 2014), or models of noticing/selective inattention (Hanna, Mullainathan, and Schwartzstein, 2014; Schwartzstein, 2014). In such models, agents fail to notice and incorporate key data points in their learning process, and if asked later, cannot recall the relevant data. In our model, farmers know the relevant data points and can recall them later (y_t) but may draw the wrong conclusion from a data point (attributing y_t to $F(y|b)$ when y_t was achieved using good quality fertilizer) due to random chance. Understanding that there is some overlap in the $F(y|b)$ and $F(y|g)$ distributions, the farmer may choose to ignore a data point if the relative likelihood of one distribution over another is not sufficiently high. We simulate several choices of γ to characterize how it affects the learning process.

We could model the farmer's beliefs as a single prior following the Beta distribution, as is standard when modeling beliefs formed by observing the outcomes of a series of Bernoulli trials (Gelman et al., 2014). The Beta distribution is characterized by two hyperparameters, α and β, with $\alpha - 1$ indicating the number of prior successes observed and $\beta - 1$ indicating the number of former failures. When α and β are both set to 1, the Beta distribution is identical to the uniform distribution. The farmer's beliefs about the prevalence of good quality fertilizer – beliefs about p – are given in period 0 by $g(p_0) \sim \text{Beta}(\alpha_0,\ \beta_0)$. If the farmer observes a single success, the posterior will be updated by Bayes' Rule to be $g(p_1) \sim \text{Beta}(\alpha_0 + 1,\ \beta_0)$; if instead the farmer observes a failure, the posterior will be updated to be $g(p_1) \sim \text{Beta}(\alpha_0,\ \beta_0 + 1)$. After observing n trials of which y are deemed successes, the farmer's beliefs will be $g(p_t) \sim \text{Beta}(\alpha_0 + y,\ \beta_0 + n - y)$. The mean of the Beta distribution is $\frac{\alpha}{\alpha+\beta}$, so in the limit, beliefs will converge to the fraction of successes observed, $\frac{y}{n}$. The variance of the Beta distribution is $\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} = \frac{(y)(n-y)}{(n)^2(n+1)}$, which converges to zero as the number of trials increases at the rate of $\frac{1}{n}$ ((Gelman et al., 2014) page 35). Thus the

standard Bayesian updating model of data observed from Bernoulli trials does not allow a full examination of the uncertainty of beliefs because the uncertainty of beliefs necessarily collapses at a fixed rate.

We allow for uncertainty in beliefs by assuming the farmer holds multiple beliefs about the rate of good fertilizer.[28] Specifically, at time t the farmer holds a set of beliefs $\mathcal{P}_t = \{p_t^1, p_t^2, p_t^3, ...p_t^n\}$ about p, the prevalence of good fertilizer in the market. Each prior follows its own Beta distribution. We think of each prior as seeded by a different source of information about fertilizer quality. For example, a neighbor might have shared that their crops performed poorly after trying fertilizer, an extension agent recommended using fertilizer for higher yields, a newspaper article reported on a study on the prevalence of counterfeit fertilizer, while their agri-dealer tried to sell them on the yield-increasing qualities of fertilizer. Experimental studies have shown that people in general have difficulty reducing compound lotteries[29] in laboratory and lab-in-the-field settings ((Halevy, 2007) (Machina and Siniscalchi, 2014) (Elabed and Carter, 2015) (Bland and Rosokha, 2019)), so it is not a strong assumption that the farmer in our model may not combine information from multiple sources

[28]The idea of modeling uncertainty about the likelihood of an outcome (also known as ambiguity) as multiple priors (or multiple discrete ideas about the likelihood of an outcomes) goes back to the canonical Ellsburg urns (Ellsberg, 1961). Ellsburg's original thought experiment asked participants to consider two urns: the first contains ten balls that are a mix of black and red balls, but you do not know how many of each; the second contains precisely five red and five black balls. For a $100 prize, Ellsburg asked the following four questions: 1) which would you rather bet on: drawing a Red ball from Urn 1 or a Black ball from Urn 1?; 2) Red from Urn 2 or Black from Urn 2?; 3) Red from Urn 1 or Red from Urn 2?; Black from Urn 1 or Black from Urn 2? Most people who Ellsberg interviewed said they were indifferent in the first two questions, but prefer Red 2 to Red 1, and Black 2 to Black 1. This is a violation of rationality under the Savage Axioms: choosing Red 2 to Red 1 implies the subject believed there are fewer red balls in Urn 1 than black balls, while choosing Black 2 to Black 1 implies the opposite. Most notable for our purposes, drawing out this aversion to ambiguity involved asking subjects to evaluate their beliefs about the relative number of black and red balls in an urn; this is equivalent to asking them to form multiple discrete ideas about the likelihood of an outcomes, or multiple priors. (Halevy, 2007) provides a nice description of the evolution of mathematical models of ambiguity aversion, beginning with early models with discrete multiple priors such as (Gilboa and Schmeidler, 1989) and only 15 years later models with continuous probability distributions such as (Klibanoff, Marinacci, and Mukerji, 2005).

[29]Multiple authors, both theorists and empiricists, have shown that aversion to ambiguity is synonymous with the failure to reduce compound lotteries. In the canonical Ellsburg urn thought experiment, the "first order" lotteries for Urn 1 are the possibilities of 0 red and 10 black balls, 1 red and 9 black balls, ..., 9 red and 1 black balls, and 10 red and 0 black balls in the urn. The "second order" lottery is the agent's subjective belief about the likelihood of each "first order" lottery. The Savage axioms of Subjective Expected Utility theory assume that the agent would weight each of the "first order" lotteries by their relative likelihood in the "second order" lottery, and behave as if this weighted average of likelihoods were the single lottery they faced. This notion is easily generalized to continuous probability distributions as in (Klibanoff et al., 2005) with the assumption of a linear second order utility function.

into one prior but rather maintains and updates multiple priors. Several empirical papers have demonstrated that ambiguity averse farmers are less likely to adopt new technologies ((Elabed and Carter, 2015), (Ward and Singh, 2015), (Barham et al., 2014), (Ross et al., 2012), (Engle-Warnick et al., 2007)); we suggest here that if the farmers in our model are ambiguity averse, then the extent to which their multiple discrete prior beliefs remain diffuse will further impede their interest in using fertilizer.

3.2 Simulation Results

We simulate the evolution of a farmer's beliefs first using a uniform prior to represent an uninformative prior, then with multiple priors as an alternative representation of an uninformative prior. We then vary parameters to explore which elements of the model best explain the three stylized facts.

The simulation requires several parameter values: the number of time periods over which the farmer learns,[30] the number and shape of beliefs about the rate of good quality fertilizer, the caution parameter, the distributions of expected yields using good and bad fertilizer, and the true distribution from which yields are drawn. Table 4 provides these values.

The way the simulation works is:

1. Initialize parameter values of $F(y|g)$, $F(y|b)$, the true yield distribution $F(y)$, and initial belief values $\mathcal{P}_0$,
2. For each time period $t \in \{1, T\}$,
   (a) Draw a yield y_t from the true yield distribution.
   (b) Calculate $L(F(y|g)|y_t)$ and $L(F(y|b)|y_t)$.
   (c) Compare $L(F(y|g)|y_t)$ and $L(F(y|b)|y_t)$ and categorize the fertilizer quality as good, bad, or uninformative according to Equation (1).

[30] We simulate the possibility of a single yield observation per period, but because the Beta distribution depends on the total number of successes and failures observed, simulating more observations per period is synonymous with simulating more periods.

(d) Update the α_t and β_t parameters of each belief $p_t \in \mathcal{P}_t$; $\alpha_{t+1} = \alpha_t + 1$ and $\beta_{t+1} = \beta_t$ if the fertilizer quality was categorized as good; $\alpha_{t+1} = \alpha_t$ and $\beta_{t+1} = \beta_t + 1$ if the fertilizer quality was categorized as bad; $\alpha_{t+1} = \alpha_t$ and $\beta_{t+1} = \beta_t$ if yield was categorized as uninformative.

(e) Form $\mathcal{P}_{t+1}$ and repeat at (a).

Table 4: Simulation Parameters, Values, and Sources

Input	Purpose	Baseline Value	Source
T	Number of periods	50	25 years of growing seasons
Priors	Starting beliefs about rate of good quality fertilizer	Uniform prior Multiple priors	Choices of uninformative priors
γ	Caution parameter: governs willingness to consider yield informative about quality	2	75% of yields informative
$F(y\|g)$	Expected yield distribution using good fertilizer	$\mathcal{N}(2012, (\frac{266}{255} * 2012)^2)$	TZ yield expectations
$F(y\|b)$	Expected yield distribution using bad fertilizer	$\mathcal{N}(778, (\frac{266}{255} * 778)^2)$	TZ yield expectations
$F(y)$	Distribution from which yields are drawn	$\mathcal{N}(2012, (\frac{266}{255} * 2012)^2)$	TZ yield expectations

For each specification we set the number of periods to 50; given that Tanzania, like many other countries in the region, has two production seasons per year, 50 periods can be thought of as representing 25 years of growing seasons in East Africa. The caution parameter is set to $\gamma = 2$ under which 75% of yields are deemed informative. When we simulate a single prior, it is initially set to the uniform distribution. When we simulate multiple priors, the first prior has an expectation of $p_1 = 0.1$, the second an expectation of $p_2 = 0.2$, all the way to the ninth with an expectation of $p_9 = 0.9$. The variance of each prior is set to $p_i(1-p_i)/10$.[31,32,33] The expected distribution of yields using good fertilizer is set to $\mathcal{N}(2012, (\frac{266}{255} * 2012)^2)$. The mean yield was set to the mean yield expected by the Tanzanian farmers when using the best quality fertilizer. The variance of the good yield distribution was set to match the relative

[31] We choose the specific values for α and β to match the mean and variance of these priors

[32] We normalize the variance by 10 to account for the adaptation between the binomial and beta distributions.

[33] Figure 8 in the appendix shows the evolution of beliefs with 9 priors as specified here, as well as three priors seeded at 0.1, 0.5, and 0.9, and three priors seed at 0.3, 0.5, and 0.7.

variance of yields reported in our Ugandan data. The expected distribution of yields using bad fertilizer is set to $\mathcal{N}(778, (\frac{266}{255} * 778)^2)$, with the mean yield set to be what Tanzanian farmers expected when using bad quality fertilizer and the variance scaled to match Ugandan maize yields. We assume that the true fraction of good fertilizer is 1 and true yields are drawn from $\mathcal{N}(2012, (\frac{266}{255} * 2012)^2)$ because nearly all fertilizer in the region has been found to be high quality; thus if beliefs were accurate, p_t would converge to 1.

The statistics of interest at the end of the simulations are: (1) what does the farmer believe, and (2) what is the range in the farmer's beliefs? In the figures that follow, we show the interquartile range of the single prior, or the interquartile range of the highest and lowest of the multiple priors along with the average of the multiple priors. Each time we run a simulation, the statistics of interest vary due to the stochasticity in the model, so we run each simulation 1,000 times and average over them.

Figure 4 presents the results of four baseline simulations, with beliefs shown on the y-axis and the number of time periods on the x-axis. The top row of figures show simulations when $\gamma = 1$, or when caution is minimal and all yields are deemed informative. The bottom row of figures show simulations when $\gamma = 2$ and only 75% of yields are deemed informative. The left panels show simulations of a single prior seeded with the uniform distribution. The right panels show simulations of nine multiple priors initially spread evenly through the unit interval.

The single prior panels show that while beliefs narrow and improve (become closer to 1) initially, they converge to a level that is far from the true proportion of good fertilizer in the market (1). This occurs because when the farmer observes a poor yield, he sometimes attributes it to bad fertilizer rather than an unlucky season; beliefs about the proportion of good fertilizer in the market converge to a level proportionate to the overlap between the good and bad fertilizer yield distributions. The multiple prior panels show a similar story: beliefs initially narrow, but converge to a level that is far from the truth. The multiple prior panels also demonstrate that when the initial non-informative prior is seeded as multiple priors rather than the uniform distribution, significant uncertainty in beliefs remains even after observing the yields from 50 growing seasons (25 years).

Comparing the top and bottom rows of Figure 4 show that when the farmer is aware that he may misattribute a poor yield draw to bad fertilizer and exercises caution in interpreting yields, beliefs do converge to a higher (more accurate) level. However, because only 75% of yields are deemed informative when caution is exercised ($\gamma = 2$), the interquartile range of the single prior is wider than when caution is not exercised, and the spread and interquartile ranges of the multiple priors are also wider. This indicates that there is a tension between proper attribution and certainty in beliefs. When the farmer knows that it's difficult to learn in a highly stochastic environment, his beliefs do become more accurate, but he is less certain of them because he declares fewer yields to be informative.

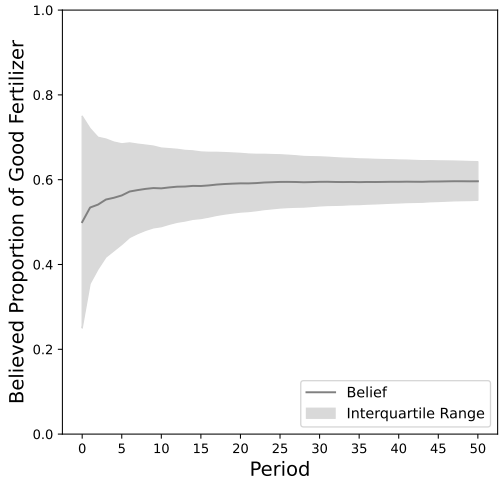
This tension between proper attribution and certainty in beliefs presents a problem for policymakers interested in encouraging fertilizer use. On the one hand, informing farmers about the problem of misattribution and encouraging them to use caution when interpreting yield outcomes could improve beliefs, which should encourage use due to waning risk aversion. On the other hand, encouraging caution worsens certainty in beliefs, which should discourage use due to increased ambiguity aversion. It is not a priori clear which effect would dominate.

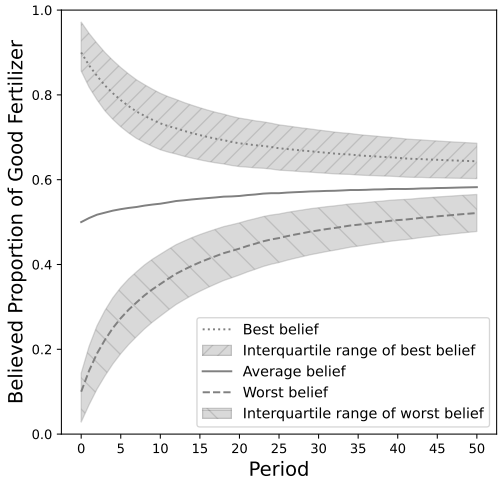
Our choices for the mean yield parameters for the baseline simulations are based on Tanzanian farmers' reported yield expectations using the best quality (2012 kilograms per hectare) and bad quality (778 kilograms per hectare) fertilizer. However, these yields are considerably lower than what was observed in the Bold et al. (2017) grow-out trials in Uganda, and the difference between yields with high quality fertilizer (4400 kilograms per hectare in the grow-out trial) and no fertilizer (1820 kilograms per hectare) was larger in the grow-out trials than in farmer's expectations. Additionally, our baseline simulations show belief evolution over only 50 periods (25 years). Might learning improve if farmers expected and observed yields more in line with grow-out trials and observed many more data points?

Figure 5 shows simulations that are seeded with data from the Bold et al. (2017) grow-out trials rather than farmers' reported yield expectations and runs those simulations for 100 periods (50 years). This in essence shows simulations of learning under the very best possible circumstances. As expected, beliefs are substantially closer to the truth when farmers observe yields in line with those from grow-out trials, but they do not converge to fully accurate beliefs

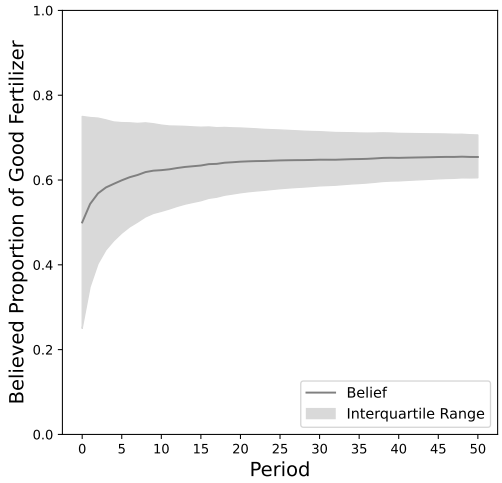
Figure 4: Evolution of beliefs with and without multiple priors

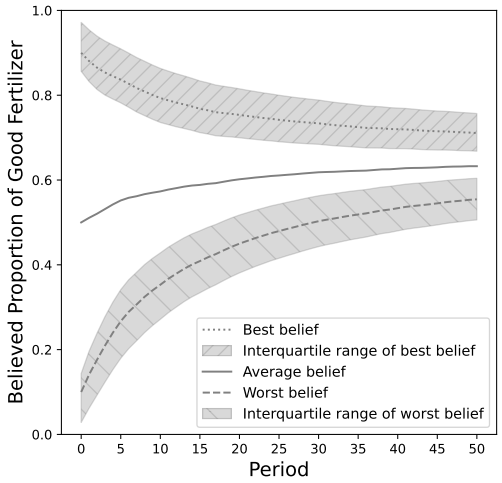
(a) No caution ($\gamma = 1$) and a single prior (b) No caution ($\gamma = 1$) and multiple priors





(c) Some caution ($\gamma = 2$) and a single prior (d) Some caution ($\gamma = 2$) and multiple priors





Notes: The figure shows simulations of the belief updating model over 50 periods with yield distributions calibrated to what Tanzanian farmers say they expect from using the best and bad fertilizer. The first row of panels show belief evolution when farmers do not exercise caution in interpreting yield outcomes ($\gamma = 1$) while the second row shows that happens when farmers ignore the 25% of yields that are most difficult to interpret ($\gamma = 2$). The left panels show beliefs seeded with an initial prior of the uniform distribution. The right panels show beliefs seeded with 9 multiple priors spread evenly through the unit interval.

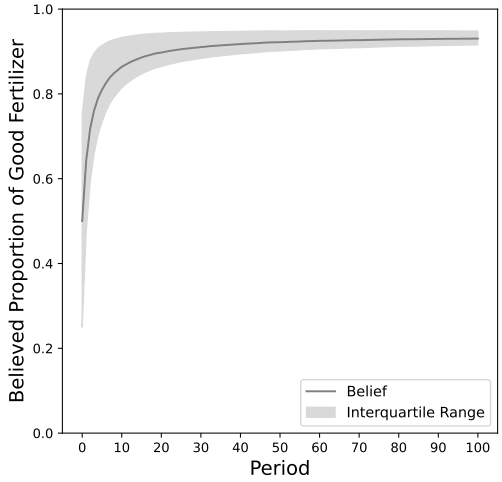
(perfect quality fertilizer). This occurs because when the yield distributions using and not using fertilizer overlap at all, there will always be scope for misattribution. Additionally,

when seeded with multiple priors, considerable uncertainty in beliefs remains. Thus even when farmers are able to observe higher yields and expect a bigger yield improvement to using fertilizer, beliefs still do not fully converge to an accurate and certain belief.

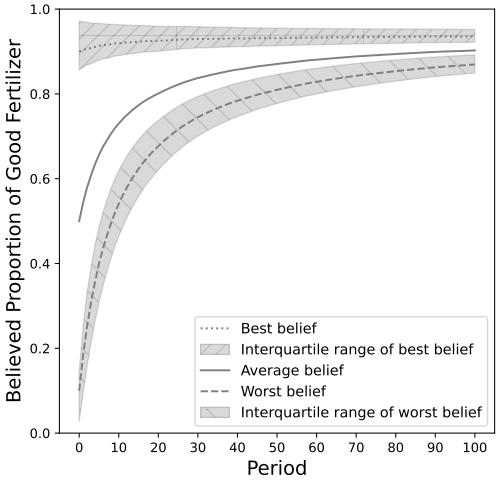
In summary, our belief updating model and its simulation show that even when farmers begin with no clear idea about the true ratio of good and bad fertilizer in the market (modeled either by a single uniform distribution prior or multiple priors spread evenly through the unit interval) and observe yields consistent with those obtained by professional agronomists in grow-out trials for 50 years, their beliefs still do not converge to the truth that all of the fertilizer in their local market is good, nor do they converge with certainty on an incorrect belief. When misattribution and uncertainty in beliefs are present, learning is not possible.

Figure 5: Evolution of beliefs with grow-out trial yield distributions

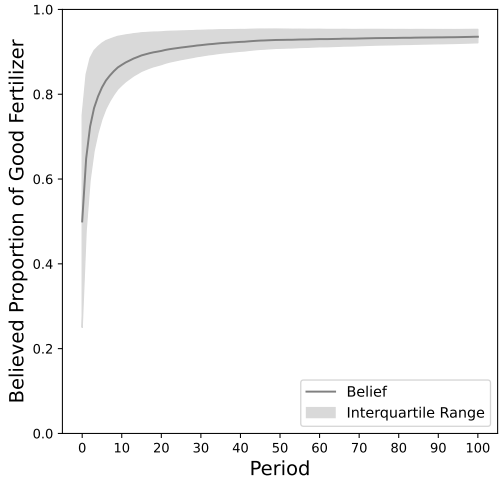
(a) No caution ($\gamma = 1$) and a single prior



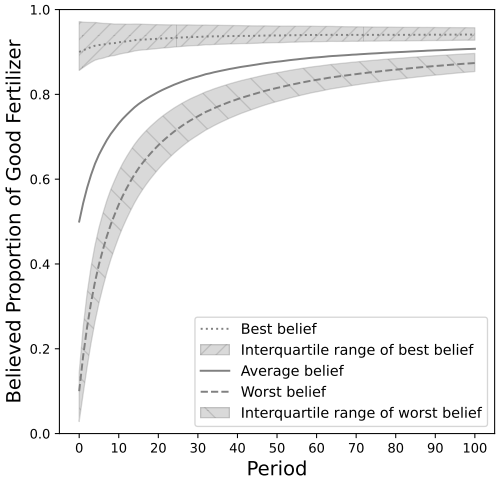
(b) No caution ($\gamma = 1$) and multiple priors



(c) Some caution ($\gamma = 1.4$) and a single prior



(d) Some caution ($\gamma = 1.4$) and multiple priors



Notes: The figure shows simulations of the belief updating model over 100 periods with yield distributions calibrated to the yield curves obtained in the Bold et al. (2017) grow out trials in Uganda. The first row of panels show belief evolution when farmers do not exercise caution in interpreting yield outcomes ($\gamma = 1$) while the second row shows that happens when farmers ignore the 25% of yields that are most difficult to interpret ($\gamma = 1.4$). The left panels show beliefs seeded with an initial prior of the uniform distribution. The right panels show beliefs seeded with 9 multiple priors spread evenly through the unit interval.

3.3 Testing Model Implications

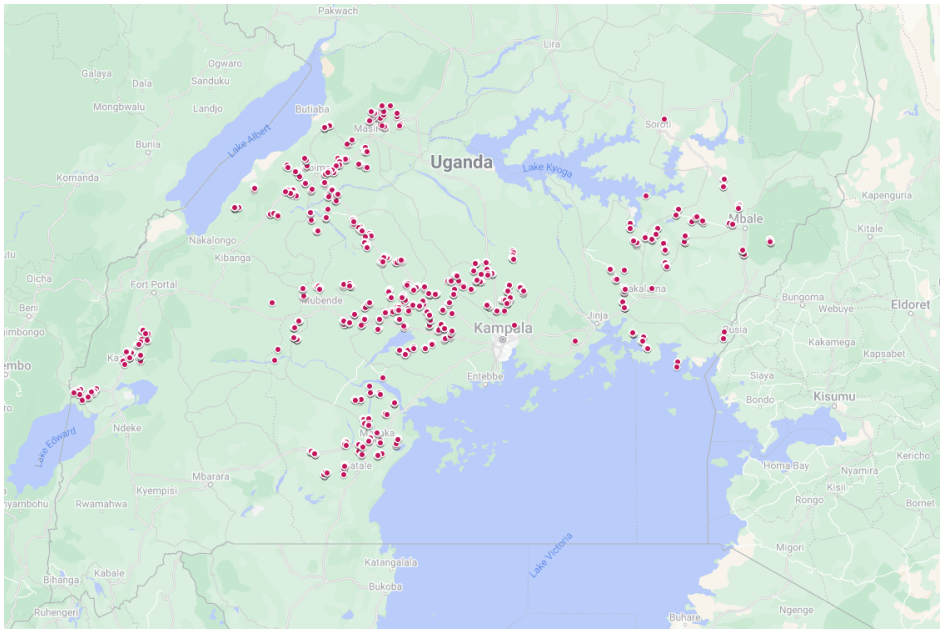
The simulations provide a testable hypothesis that we take to our Uganda data: all else equal, farmers who live in areas with more variable rainfall will believe more fertilizer is bad and will be more uncertain of beliefs. More variable rainfall makes it more likely that an individual farmer will experience 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 range of opinions about the quality of fertilizer.

We bring these insights to 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, providing daily precipitation for 5.5 km^2 cells. We gathered precipitation data for the 10 years prior to the survey in 2014. We calculated precipitation variation 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 the possibility that severe, low-tail events are easily attributable to non-fertilizer causes.[34] 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. Figure 6 shows the geographic distribution of households in the Uganda sample.

Table 5 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

[34]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 B.

Figure 6: Households reporting beliefs in Uganda



Notes: The figure shows a map of households locations in the Uganda dataset.

season, as well as demographic and farming controls.[35] 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.

$$Belief_{iv} = \beta_0 + \beta_1 RainfallVariation_{iv} + \beta_2 Demographics_i + \beta_3 Farming_i + \epsilon_{iv} \qquad (2)$$

We also find that rainfall variability is highly correlated with the standard deviation and

[35]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.

range of beliefs, suggestive evidence that variable rainfall is also related to uncertainty in beliefs. On average, the range between a farmer's 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 farmer's beliefs by 0.014, a 5.2% increase.

Table 5: Relationship between precipitation variation and beliefs about fertilizer quality: Uganda

VARIABLES	(1) Mean belief	(2) StDev beliefs	(3) Range beliefs
Historic variance in precipitation:	-0.26***	0.07***	0.21***
First season - Excluding below 2SD	(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

Notes: The table presents the relationship between beliefs and historic rainfall variation in Uganda. Column 1 shows the mean belief about the fraction of fertilizer good in the local market is negatively related to rainfall variation, while columns 2 and 3 show that the standard deviation and range of individual farmers' beliefs are positively related to historic rainfall variation.

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.

4 Conclusion

Agents can find it difficult to learn about a product's quality or efficacy. In this paper we explore two mechanisms that frustrate learning about quality. First, in the presence of noise in the process that converts inputs to outputs, an agent may mistakenly attribute a bad outcome to an input's quality when the bad outcome was actually caused by either

natural variation or a different part of the production process. We call this phenomenon misattribution. Second, learning is further complicated when the agent is unsure about the likelihood that the input quality is good or bad; this ambiguity can be modeled by the agent holding multiple priors representing possible beliefs. We combine misattribution with multiple priors in a model of farmer learning about product quality. Our model simulations show that in the presence of both misattribution and multiple priors beliefs may never converge to the truth and may remain uncertain even after observing many new data points. Our model and its conclusions are relevant to any circumstance in which an agent cannot be immediately sure if the product they used delivered a benefit given the presence of numerous factors affecting outcomes.

We use the example of a farmer forming beliefs about the quality of fertilizer in their local market, and 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. In addition, farmers are 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 farmers were not incentivized to accurately report their beliefs in our beliefs elicitation, 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 whose quality had been tested and validated in a lab. 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 an important association suggested by the model: farmers who live in regions with greater precipitation variation 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 some experience goods can in fact be better understood as credence goods. Other examples of this phenomenon include other agricultural inputs such as hybrid seeds and pesticides as well as drugs, vaccines, vitamins, car repairs, and education. Our insights 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. However, if an environmental shock interferes with rebuilding, the fisherman may later trust the policy's effectiveness less because he misattributes the poor outcome to a poor policy rather than bad luck.[36] 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.

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. A recent short-term study of fertilizer and improved maize seed subsidy program in Mozambique showed that targeted farmers did increase their usage of fertilizer and beliefs about the efficacy of the input package in the year following the subsidy, but the effects showed some indication of fading out in the second year after the subsidy (Carter, Laajaj, and Yang, 2021). This is consistent with our model, especially if the year in which the input package was subsidized happened to be a good growing year. After an initial observation of high yields, farmers attribute the high yields to high quality and/or

[36] We thank Kira Lancker for this example.

high efficacy inputs. Subsequent years are independent draws from the yield distribution, so they may naturally be lower than the year in which the subsidy was delivered; in that case, beliefs about the quality or efficacy of inputs will wane in time. 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.

Our willingness-to-pay experiment is akin to a certification program and 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 of unverified nutrient content. 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 as labeled on the package (Gilligan and Karachiwalla, 2021); they find that the verification program increased use of the tagged products, improved beliefs about product quality, and improved actual product 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 continues to believe that tagged products are of higher quality, though some uncertainty remains.

Even so, certification programs add costs likely to be passed on as increased product costs for farmers. Gilligan and Karachiwalla (2021) also find economically significant fertilizer price increases. Moreover, recent work by Abay, Barrett, Kilic, Moylan, Ilukor, and Vundru (2022) suggests that farmers given GPS-based measures of their plot size fail to update their beliefs about plot size; when they do update they do so asymmetrically, where farmers who underestimated plot size relative to the GPS measure more likely to update than those who over-estimated. Information does not always lead individuals to update priors toward the truth (a point bourne out in our theory and simulations and also discussed in Abay, Wossen, Abate, Stevenson, Michelson, and Barrett (2022)). A policy that increased costs without necessarily reducing or resolving uncertainty about product quality could further impede fertilizer use.

Another approach might be to make the learning process more explicit so that farmers more easily understand the causal model associated with fertilizer use – that both genetic and environmental factors contribute to crop yield outcomes and one must be deliberate to distinguish them and to not misattribute. Extension might work to make farmers attentive to the stochastic nature of production, to convince them that a single bad outcome may be indicative of bad luck rather than a bad input – realistic trial plots showing performance of new products under varying local growing conditions could be an example. However, our model also demonstrates that while interventions like these may be successful in increasing "caution" and therefore reducing misattribution, so long as farmers keep multiple opinions in mind via multiple priors, there is a trade-off between accurate beliefs and certainty in those beliefs. Calling attention to the stochastic nature nature of yields may improve use by reducing misattribution, but may worsen use through increased uncertainty in beliefs.

Programs that reduce uncertainty in beliefs could offer another pathway. Maertens et al. (2022) implemented a low-cost and low-touch information campaign in markets in Tanzania, posting the results of urea fertilizer testing and sharing them with farmers in village meetings. They find strong effects on farmers' beliefs about urea quality and also extensive margin effects on fertilizer purchasing and use; farmers who had not used fertilizer drive estimated effects. The effect of the program may have been to reduce the likelihood that farmers misattribute bad yield outcomes to fertilizer quality as they had some confidence that fertilizer had been tested and found to be good in their local market.

Not all farmers have incorrect beliefs about urea quality. Understanding the heterogeneity across farmers and the spatial patterns in beliefs within and across villages could provide insight into the learning process and possible belief herding over time. Our work suggests that future research into the source of incorrect beliefs about product quality and methods to correct such beliefs is warranted.

References

Abay, K. A., C. B. Barrett, T. Kilic, H. Moylan, J. Ilukor, and W. Vundru (2022). Non-classical measurement error and farmers response to information reveal behavioral anomalies. *Working Paper*.

Abay, K. A., T. Wossen, G. A. Abate, J. Stevenson, H. Michelson, and C. B. Barrett (2022). Inferential and behavioral implications of measurement error in agricultural data. *Annual Review of Resource Economics*.

Ashour, M., L. Billings, D. O. Gilligan, A. Jilani, and N. Karachiwalla (2019). An evaluation of the impact of e-verification on counterfeit agricultural inputs and technology adoption in Uganda: Fertilizer testing report. Technical report, International Food Policy Research Institute.

Ashour, M., L. Billings, D. O. Gilligan, and N. Karachiwalla (2015). Evaluation of the impact of e-verification on counterfeit agricultural inputs and technology adoption in Uganda. Technical report, International Food Policy Research Institute.

Ashour, M., D. O. Gilligan, J. B. Hoel, and N. I. Karachiwalla (2019). Do beliefs about herbicide quality correspond with actual quality in local markets? Evidence from Uganda. *The Journal of Development Studies 55*(6), 1285–1306.

Barham, B. L., J.-P. Chavas, D. Fitz, V. R. Salas, and L. Schechter (2014). The roles of risk and ambiguity in technology adoption. *Journal of Economic Behavior & Organization 97*, 204–218.

Becker, G. M., M. H. Degroot, and J. Marschak (1964). Measuring utility by a single-response sequential method. *Behavioral Science 9*(3), 226–232.

Bland, J. and Y. Rosokha (2019). Learning Under Uncertainty with Multiple Priors: Experimental Investigation. Working Paper.

Bold, T., K. C. Kaizzi, J. Svensson, and D. Yanagizawa-Drott (2017). Lemon technologies and adoption: Measurement, theory and evidence from agricultural markets in Uganda. *The Quarterly Journal of Economics 132*(3), 1055–1100.

Bravo-Ortega, C. and D. Lederman (2005). *Agriculture and national welfare around the world: Causality and international heterogeneity since 1960*. The World Bank.

Bumb, B., J. Ariga, M. Anand, A. Cameron, and N. Nkonya (2021). Assessment of the fertilizer market and bulk procurement system in the united republic of tanzania.

Byerlee, D., A. De Janvry, and E. Sadoulet (2009). Agriculture for development: Toward a new paradigm. *Annual Review of Resource Economics 1*, 15–31.

Carter, M., R. Laajaj, and D. Yang (2021). Subsidies and the african green revolution: Direct effects and social network spillovers of randomized input subsidies in mozambique. *American Economic Journal: Applied Economics 13*(2), 206–29.

Carter, M. R., R. Laajaj, and D. Yang (2013). The impact of voucher coupons on the uptake of fertilizer and improved seeds: Evidence from a randomized trial in Mozambique. *American Journal of Agricultural Economics 95*(15), 1345–1351.

Diao, X., S. Fan, D. Headey, M. Johnson, A. N. Pratt, and B. Yu (2008). *Accelerating Africa's food production in response to rising prices: Impacts and requisite actions.* International Food Policy Research Institute.

Dorosh, P., H. G. Wang, L. You, and E. Schmidt (2012). Road connectivity, population, and crop production in Sub-Saharan Africa. *Agricultural Economics 43*(1), 89–103.

Duflo, E., M. Kremer, and J. Robinson (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from kenya. *American Economic Review 101*(6), 2350–90.

Dzanku, F. M., M. Jirström, and H. Marstorp (2015). Yield gap-based poverty gaps in rural Sub-Saharan Africa. *World Development 67*, 336–362.

Elabed, G. and M. R. Carter (2015). Compound-risk aversion, ambiguity and the willingness to pay for microinsurance. *Journal of Economic Behavior & Organization 118*, 150–166.

Ellsberg, D. (1961). Risk, ambiguity, and the savage axioms. *The Quarterly Journal of Economics*, 643–669.

Engle-Warnick, J. C., J. Escobal, and S. Laszlo (2007). Ambiguity aversion as a predictor of technology choice: Experimental evidence from Peru. *Working Paper*.

Engle-Warnick, J. C., J. Escobal, and S. C. Laszlo (2011). Ambiguity aversion and portfolio choice in small-scale Peruvian farming. *The B.E. Journal of Economic Analysis & Policy 11*, 1–56.

Epstein, L. G. and M. Schneider (2007). Learning Under Ambiguity. *The Review of Economic*

Studies 74(4), 1275–1303.

Esponda, I. and D. Pouzo (2021). Equilibrium in misspecified Markov decision processes. *Theoretical Economics 16*(2), 717–757.

FAOStat (2021). FAOStat.

Foster, A. D. and M. R. Rosenzweig (2010). Microeconomics of technology adoption. *Annual Review of Economics 2*(1), 395–424.

Funk, C., P. Peterson, M. Landsfeld, D. Pedreros, J. Verdin, S. Shukla, G. Husak, J. Rowland, L. Harrison, A. Hoell, and J. Michaelsen (2015, December). The Climate Hazards Infrared Precipitation with Stationsa new environmental record for monitoring extremes. *Scientific Data 2*(1), 150066.

Gabaix, X. (2014). A sparsity-based model of bounded rationality. *Quarterly Journal of Economics 129*(4), 1611–1710.

Gelman, A., J. B. Carlin, H. S. Stern, D. B. Dunson, A. Vehtari, and D. B. Rubin (2014). *Bayesian Data Analysis* (Third ed.). CRC Press.

Gharib, M. H., L. H. Palm-Foster, T. J. Lybbert, and K. D. Messer (2021). Fear of fraud and willingness to pay for hybrid maize seed in kenya. *Food Policy 102*, 102040.

Gilboa, I. and D. Schmeidler (1989). Maxmin expected utility with non-unique prior. *Journal of Mathematical Economics 18*(2), 141–153.

Gilligan, D. and N. Karachiwalla (2021). Product assurance and product quality: Evidence from agricultural technologies. *Working paper*.

Halevy, Y. (2007). Ellsberg revisited: An experimental study. *Econometrica 75*(2), 503–536.

Hanna, R., S. Mullainathan, and J. Schwartzstein (2014). Learning through noticing: Theory and evidence from a field experiment. *Quarterly Journal of Economics 129*(3), 1311–1353.

Harou, A. P., M. Madajewicz, H. Michelson, C. A. Palm, N. Amuri, C. Magomba, J. M. Semoka, K. Tschirhart, and R. Weil (2022). The joint effects of information and financing constraints on technology adoption: Evidence from a field experiment in rural tanzania. *Journal of Development Economics 155*, 102707.

Heidhues, P., B. Kőzegi, and P. Strack (2018). Unrealistic expectations and misguided learning. *Econometrica 86*(4), 1159–1214.

Kala, N. (2019). Learning, adaptation, and climate uncertainty: Evidence from Indian agriculture. *Working paper*.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics 129*(2), 597–652.

Klibanoff, P., M. Marinacci, and S. Mukerji (2005). A smooth model of decision making under ambiguity. *Econometrica 73*(6), 1849–1892.

Kohler, J. (2020). Assessment of fertilizer distribution systems and opportunities for developing fertilizer blends.

Krishnan, P. and M. Patnam (2013). Neighbors and extension agents in Ethiopia: Who matters more for technology adoption? *American Journal of Agricultural Economics 96*(1), 308–327.

Langyintuo, A. S., W. Mwangi, A. O. Diallo, J. MacRobert, J. Dixon, and M. Bnziger (2010). Challenges of the maize seed industry in Eastern and Southern Africa: A compelling case for private-public intervention to promote growth. *Food Policy 35*(4), 323–331.

Liu, E. M. (2012). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. *The Review of Economics and Statistics 95*(4), 1386–1403.

Liu, E. M. and J. Huang (2013). Risk preferences and pesticide use by cotton farmers in China. *Journal of Development Economics 103*, 202–215.

Machina, M. J. and M. Siniscalchi (2014). Ambiguity and ambiguity aversion. In *Handbook of the Economics of Risk and Uncertainty*, Volume 1, pp. 729–807. Elsevier.

Maertens, A., C. Magomba, and H. Michelson (2022). Updating beliefs about fertilizer quality in Tanzania: Results from a market-level information campaign. *Working Paper*.

Marenya, P. P. and C. B. Barrett (2009). State-conditional fertilizer yield response on Western Kenyan farms. *American Journal of Agricultural Economics 91*(4), 991–1006.

Marinacci, M. (2002). Probabilistic Sophistication and Multiple Priors. *Econometrica 70*(2), 755–764.

Mbowa, S., K. C. Luswata, and K. Bulegeya (2015). Are Ugandan farmers using the right quality inorganic fertilizers? Technical report, Alliance for a Green Revolution in

Africa, Ugandan Ministry of Agriculture.

Michelson, H., B. Ellison, A. Fairbairn, A. Maertens, and V. Manyong (2021). Misperceived quality: Fertilizer in Tanzania. *Journal of Development Economics 148*, 102579.

Michelson, H., S. Gourlay, and P. Wollburg (2022). Non-labor input quality and small farms in Sub-Saharan Africa: A review. *World Bank Working Paper*.

Ortoleva, P. (2013). The price of flexibility: Towards a theory of thinking aversion. *Journal of Economic Theory 148*(3), 903–934.

Ross, N., P. Santos, and T. Capon (2012). Risk, ambiguity, and the adoption of new technologies: Experimental evidence from a developing country. In *International Association of Agricultural Economists*, Brazil.

Sanabria, J., J. Ariga, J. Fugice, and D. Mose (2018a). Fertilizer quality assessment in markets of Kenya. Technical report, International Fertilizer Development Center.

Sanabria, J., J. Ariga, J. Fugice, and D. Mose (2018b). Fertilizer quality assessment in markets of Uganda. Technical report, International Fertilizer Development Center.

Sanabria, J., G. Dimithè, and E. K. Alognikou (2013). *The Quality of Fertilizer Traded in West Africa: Evidence for Stronger Control*. International Fertilizer Development Center.

Schwartzstein, J. (2014). Selective attention and learning. *Journal of the European Economic Association 12*(6), 1423–1452.

Sheahan, M. and C. B. Barrett (2017). Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy 67*, 12–25.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica 79*(1), 159–209.

Suri, T. and C. Udry (2022). Agricultural technology in Africa. *Journal of Economic Perspectives 36*(1), 33–56.

Tittonell, P. and K. E. Giller (2013). When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. *Field Crops Research 143*, 76–90.

Van Campenhout, B., F. Nattembo, and K. Pauw (2018). *Evaluating the shifting priorities of Ugandas agricultural extension services: A micro perspective*, Volume 21. Intl Food

Policy Res Inst.

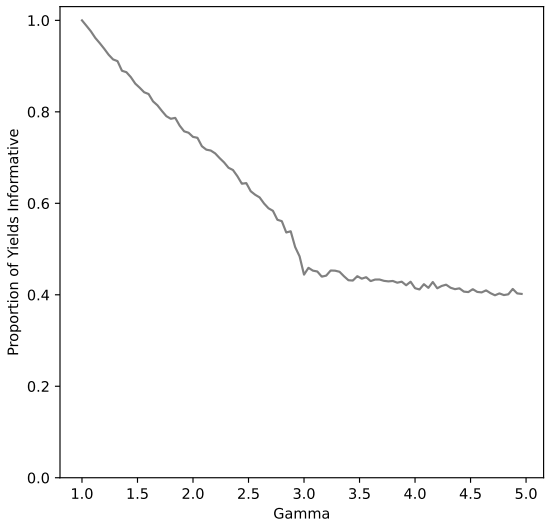
Ward, P. S. and V. Singh (2015). Using field experiments to elicit risk and ambiguity preferences: Behavioural factors and the adoption of new agricultural technologies in rural India. *The Journal of Development Studies 51*(6), 707–724.

World Bank (2009). Eastern Africa: A study of the regional maize market and marketing costs.

Zimper, A. and W. Ma (2017). Bayesian learning with multiple priors and nonvanishing ambiguity. *Economic Theory 64*(3), 409–447.

A Additional Simulations

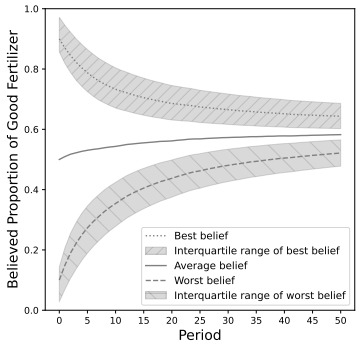
Figure 7: Fraction of yields deemed informative for varying levels of γ



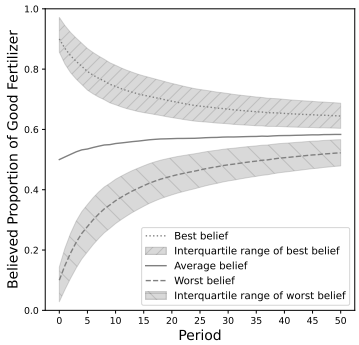
We also simulate the effects of different numbers and ranges of multiple priors. The top row of Figure 8 reproduces the baseline multiple prior simulations with nine multiple priors distributed evenly in the unit interval. The second row shows simulations of three priors, spread at means of 0.1, 0.5, 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). Beliefs in the simulations with three narrowly seeded priors converge to a narrower range than the simulations with nine priors. However, the simulations seeded with three wide priors over the same range as the baseline nine priors do not narrow substantially more than the baseline simulations.

Figure 8: Varying the number and spread of multiple priors

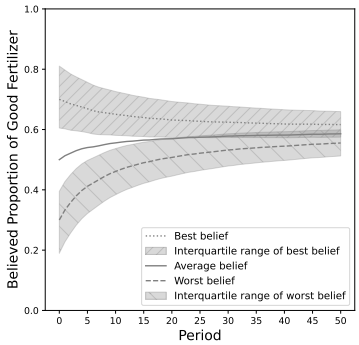
(a) 9 priors



(b) 3 wide priors



(c) 3 narrow priors



B Additional Tables

Table 6: 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 7: Willingness-to-pay for fertilizer in Tanzania

VARIABLES	(1) Baseline	(2) Adding beliefs	(3) More sure about beliefs	(4) 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 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

C Experimental Details: Tanzania

C.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

C.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 fertil-

izer 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.

D Experimental Details: Uganda

D.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 9: Belief elicitation card: Uganda

CARD 6

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**

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.