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ARTICLE

Misattribution prevents learning

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Abstract

In many markets, consumers believe things about products that are not true. We study how incorrect beliefs about product quality can persist even after a consumer has used a product many times. We explore the example of fertilizer in East Africa. Farmers believe much local fertilizer is counterfeit or adulterated; however, multiple studies have established that nearly all fertilizer in the area is good quality. We develop a learning model to explain how these incorrect beliefs persist. We show that when the distributions of outcomes using good and bad quality products overlap, agents can misattribute bad luck or bad management to bad quality. Our learning model and its simulations show that the presence of misattribution inhibits learning about quality and that goods like fertilizer with unobservable quality that are inputs into production processes characterized by stochasticity should be thought of as credence goods, not experience goods. Our results suggest that policy makers should pursue quality assurance programs for products that are vulnerable to misattribution.

KEYWORDS
beliefs, East Africa, fertilizer, input quality, learning

JEL CLASSIFICATION
C91, D83, D84, Q12

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 (Bravo-Ortega & Lederman, 2005; Byerlee et al., 2009) and will require increased use of modern agricultural inputs including chemical fertilizer. The global average nitrogen fertilizer application[1] is 70 kg per hectare; farmers in Sub-Saharan Africa average only 15 kg 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 (Esponda & Pouzo, 2010; Krishnan & Patnam, 2013), heterogeneity in returns (Marenya & Barrett, 2009; Suri, 2011), credit constraints (Carter et al., 2013; Karlan et al., 2014), and behavioral constraints (Duflo et al., 2011).[2]

Bold et al. (2017) suggest farmers do not use fertilizer because they believe that locally available fertilizers may be bad quality and therefore 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, also believe that some fertilizer in their local market is counterfeit or adulterated. 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.[3]

However, findings that farmers are willing to pay more for fertilizer of verified quality present a puzzle because most urea fertilizer in this region is good quality. 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 (Ashour, Billings, et al., 2019; Michelson, Gourlay, et al., 2023; Michelson, Magomba, & Maertens, 2023; Sanabria et al., 2018a; Sanabria et al., 2018b).[4] How do incorrect beliefs persist in equilibrium?[5]

We develop a learning model to show that misattribution can lead to the persistence of incorrect beliefs. Misattribution occurs when the distribution of outcomes from using a good-quality or bad-quality product are overlapping, and a user attributes an idiosyncratically bad outcome to the bad-quality product. We simulate the model and show that when misattribution is present, beliefs do not

[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 et al., 2013). Urea is also the fertilizer that has received the most attention in the academic literature on fertilizer quality (Ashour et al., 2015; Bold et al., 2017; Michelson et al., 2021). Urea is 46% nitrogen; most small farmer plots are in need of nitrogen, and staple cereal cultivation in Sub-Saharan Africa 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 some evidence of missing nitrogen and other nutrients in fertilizer blends and compounds, but these problems are likely attributable to manufacturing issues rather than adulteration (Sanabria et al., 2013, 2018a, 2018b). 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 (Gharib et al., 2021; Langyintuo et al., 2010).

[4]Bold et al. (2017) found that all of their samples of fertilizer had significantly lower nitrogen content than advertised, but because other larger studies have found no evidence of bad-quality fertilizer, the finding in Bold increasingly looks like an outlier in the literature. In short, the Bold study found that 100% of the 369 samples of urea fertilizer that they tested were missing nitrogen and that they were missing 30% of the nitrogen on average. Sampling and testing of urea fertilizer conducted by the International Fertilizer Development Center (the IFDC) (Sanabria et al., 2018b) and tests by the International Food Policy Research Institute (IFPRI) (Ashour, Billings, et al., 2019; Ashour, Gilligan, et al., 2019), both conducted around the same time as Bold et al., found no evidence of adulteration in Ugandan urea. The IFDC (the global experts on fertilizer sampling and quality testing) react to the Bold study and discuss the implausibly high rates of missing nitrogen from all tested samples and raise concerns about their testing methods, writing that Bold et al. "does not identify or quantify 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, 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" (Sanabria et al. 2018a). Michelson, Gourlay, et al. (2023); Michelson, Magomba, and Maertens (2023) also discusses the result and Sanabria et al.'s reaction and reviews details on testing protocols, evidence, and possible irregularities. We discuss evidence regarding fertilizer quality 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 et al., 1964)) auctions. Our focus however in this paper is understanding the result in Michelson et al. —why so many farmers believe fertilizer is bad when evidence indicates that urea fertilizer in the region is of reliably good quality.

converge to the truth, even after 1000 yield observations. 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. 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 indeed have more incorrect beliefs about fertilizer quality.

The paper begins with a discussion of urea fertilizer in East Africa, describing use in Tanzania and Uganda, and summarizing accumulating evidence regarding its good quality. We explain how Tanzanian farmers evaluate fertilizer quality, present farmers' elicited beliefs about fertilizer quality, and 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 fertilizer is bad quality when evidence finds that it is good. We simulate the model and present results. We then use data from Uganda measuring farmers' beliefs to test a key implication of our model. We conclude with a discussion of the broader implications of our results.

2 | SETTING AND DESCRIPTIVES

Fertilizers provide essential plant nutrients including nitrogen, phosphorous, and potassium to developing crops. Although fertilizers were widely adopted during the Green Revolution by 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.

2.1 | Fertilizer in East Africa

The use of chemical fertilizers in East Africa remains low (Kohler, 2020). Sheahan and Barrett (2017) document that only 16.9% and 3.2% of small farm households use fertilizer in Tanzania and Uganda, respectively. Urea was the second most widely used fertilizer in Uganda, accounting for about one sixth of the country's total fertilizer use (about 10,000 of 61,000 total tons). The NPK blend 17:17:17, which is used in sugar cane cultivation, is the most used fertilizer in Uganda by quantity, accounting for about half of all Uganda's fertilizer use. Urea is the top fertilizer used in Tanzania, accounting for more than 35% of the market by volume annually between 2008 and 2016 (Bumb et al., 2021).

Low use of fertilizers directly contributes to widespread problems of low crop yields and high rates of poverty and food insecurity (Dzanku et al., 2015; Tittonell & Giller, 2013). For example, although maize is East Africa's most important staple cereal crop (World Bank, 2009), critical as a food and feed source as well as a source of income and employment, yields remain extremely low in in the region (Diao et al., 2008; Dorosh et al., 2012): yields are approximately two metric tons per hectare, well below estimated regional yield ceilings of 4–5 metric tons per hectare (Tittonell & Giller, 2013).[6]

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 nonfertilizer 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

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

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, Billings, et al. (2019) and Ashour, Gilligan, et al. (2019)	137	0.7%
2013–2014	Uganda	Retail sellers	Bold et al., 2017	369	100%
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

Note: Table shows a summary of studies that examine the quality of urea fertilizer in East Africa and is adapted from m (Michelson, Gourlay, et al., 2023; Michelson, Magomba, & Maertens, 2023).

like salt. Counterfeiting is an extreme form of adulteration: a counterfeit bag of fertilizer is a bag of completely nonfertilizer material (pebbles, concrete, salt) sold as fertilizer. Michelson et al. (2021) emphasize that fertilizer quality is multidimensional 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 an unblended 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 both plausible adulterants for urea and cheaper than urea. For a summary of current research on fertilizer quality evidence and evaluation see Michelson, Gourlay, et al. (2023).

Previous studies have established that farmers in Sub-Saharan Africa believe there is bad-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.[7] Reports from the International Fertilizer Development Center (Sanabria et al., 2013, p. 39) conducted in several countries in East and West Africa note that farmer beliefs about the prevalence of adulterated urea are widespread but without scientific support.

Table 1 adapts a table from Michelson, Gourlay, et al. (2023) and Michelson, Magomba, and Maertens (2023), and 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 (Ashour, Billings, et al., 2019; Ashour, Gilligan, et al., 2019; Mbowa et al., 2015; Michelson et al., 2021; Sanabria et al., 2013; Sanabria et al., 2018a, 2018b). These are studies characterized by rigorous sampling at multiple levels in the supply chain and include a large number of fertilizer samples. The table

[7]Farmers are also concerned about the quality of other agricultural inputs. Ashour, Gilligan, et al. (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.

includes Michelson et al. (2021), which conducted sampling in retail shops in the same region of Tanzania as the current study.[8] Several of these studies were conducted by the International Fertilizer Development 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, Billings, et al. (2019); Ashour, Gilligan, et al. (2019) and Sanabria et al. (2018a) find no evidence of quality problems despite very similar sampling strategies.[9] Ashour, Gilligan, et al. (2019); Ashour, Billings, et al. (2019), and Bold et al. (2017) sampled from open bags and sampled widely from retailers.[10] 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 nonfertilizer 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 given that Bold et al. (2017):

> "does not identify or quantify 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, 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, perceptions of fertilizer quality are not only 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: Powdered granules, caking, and discoloration are common. Although 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 agridealer urea samples in Michelson

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

[9]Ashour, Billings, et al. (2019); Ashour, Gilligan, 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 et al. (2018) discuss OWC timing, implementation, and strategy.

[10]Although urea fertilizer is generally sold in sealed 50 and 25 kg bags, small farmers tend to purchase fertilizer in 1 or 2 kg bags. These small quantities are scooped from an open bag at the time of the transaction by agridealers or sold in repacked plastic bags prepared by agridealers 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 1 and 2 kg 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, Billings, et al. (2019) and Ashour, Gilligan, 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.

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 of the product.

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.[11] 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 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 bad 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 traveled 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.[12] A report from the International Fertilizer Development Center in 2018 on fertilizer quality in Uganda documented the phenomenon of farmers commonly attributing crop growth problems to bad-quality 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).

[11]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*.

[12]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 one field performed significantly better than the other. The farmers complained to the field director that the fertilizer that the farmer applied on the field that performed poorly was bad quality and caused 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 he 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, 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 et al., 2022).

TABLE 2 Farmer summary statistics, Uganda and Tanzania samples.

	Ugandan farmer sample	Tanzanian farmer sample
	Mean/*SD*	Mean/*SD*
Acres owned/cultivated	2.57 (3.96)	3.02 (2.06)
Ever used/bought mineral fertilizer	0.15 (0.35)	0.34 (0.48)
Used mineral fertilizer year surveyed	0.11 (0.31)	0.12 (0.32)
Observations	1388	349

Note: Summary statistics on acres owned or cultivated, historical fertilizer use, and fertilizer use in the most recent agricultural season for Uganda and Tanzanian farmers. Ugandan data were collected in 2014; Tanzanian data were collected in 2019.

2.3 | Farmers' 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).[13,14]

Table 2 presents farming summary statistics for the Uganda and Tanzania samples. 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 bad-quality fertilizer in their respective markets. Both surveys use a similar strategy for eliciting these beliefs. Enumerators asked farmers to imagine that 10 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 10 bags of fertilizer would be good quality or bad quality (counterfeit or adulterated).[15]

The farmer's report of how many bags of 10 are likely to be bad is a measure of the farmer's belief about the likelihood of buying bad-quality fertilizer. We focus on 1 kg 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 kg bags is widespread, and repackaged bags of 1 or 2 kg were available in nearly all agridealer shops visited by the study team. Farmers in the focus groups also discussed purchasing fertilizer in these small quantities.[16]

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 bad quality. Before we discuss

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

[14]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.

[15]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.

[16]Farmers in this area make their assessment at the market level rather than with respect to a specific agridealer 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 good-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 bad quality. 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.

TABLE 3 Sources of farmers' beliefs about fertilizer quality in Tanzania.

	Tanzanian farmer sample
	Mean/*SD*
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)
The media	0.01 (0.12)
Observations	349

Note: The table shows summary statistics of the information sources farmers in Tanzania report using to form their beliefs about fertilizer quality.

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—59%—say that they form beliefs based on their own opinion, *not* based on their personal results with fertilizer. 21% say they use their own experience to form beliefs, whereas 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 an extension agent. Only 1% say they form beliefs based on what they have heard or read in the media.

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.[17] Only 28% of farmers believe that all of the fertilizer in their local market is good quality. Farmers who had previously used fertilizer were more likely to report that more of the fertilizer in their local market was good quality, whereas those who had never purchased fertilizer were more likely to say that more fertilizer in their local market was bad quality. 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 quality, whereas those who said they formed beliefs based on what others told them thought more local fertilizer was bad quality.

In Uganda, farmers believe 65% of the fertilizer in their local market is good quality. Figure 1b shows the distribution of beliefs with a vertical dashed line indicating the mean.[18] 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 quality. Male farmers, older farmers, and those who owned more land were also more likely to say that local fertilizer was good quality.

2.4 | Farmers' willingness to pay for fertilizer

We conducted a binding Becker-Degroot-Marschak (BDM; Becker et al., 1964) auction willingness-to-pay experiment with our sample of Tanzanian farmers.[19] We use the results of our experiment to

[17]Tanzanian farmers who have not used fertilizer before believe that 64% is good, whereas those who have used fertilizer before believe that 72% is good. Figure B.1a in the Online Appendix shows the distribution of beliefs for those who have and have not used fertilizer in Tanzania.
[18]Ugandan farmers who have not used fertilizer before believe that 64% is good, whereas those who have used fertilizer before believe that 68% is good. Figure B.1b in the Online Appendix shows the distribution of beliefs for those who have and have not used fertilizer in Uganda.
[19]Burchardi et al. (2021) tested four variants of the BDM in rural Uganda and found that comprehension was high, and all four yielded similar measures of willingness to pay.

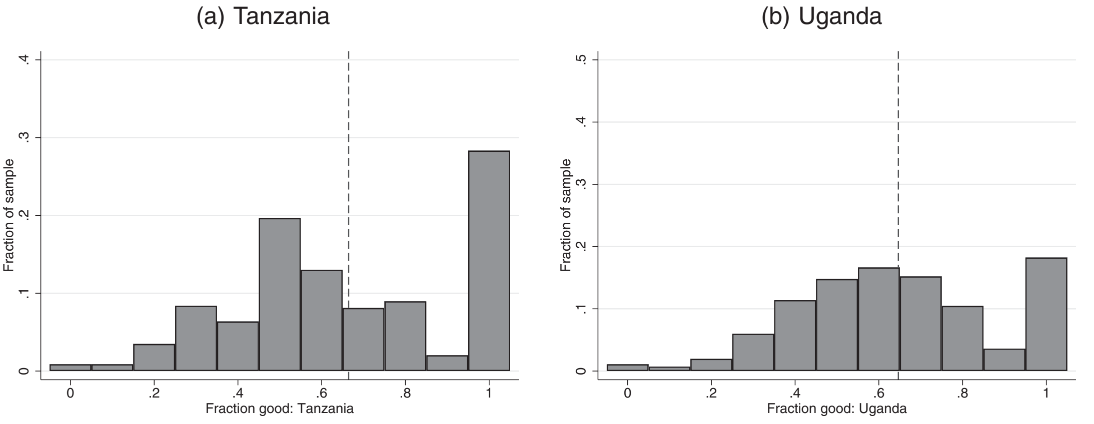

FIGURE 1 Beliefs about fertilizer quality. The first subfigure shows a histogram of Tanzanian farmers' stated beliefs about the fraction of fertilizer that is good in their local market, with a dashed line indicating the mean belief. The figure shows that although 28% of farmers believe all of the fertilizer in their local market is good, on average farmers think that only 66% of fertilizer available to them is good. The second subfigure shows a histogram of Ugandan farmers' stated beliefs about the fraction of fertilizer that is good in their local market, with a dashed line indicating the mean belief. The figure shows that whereas 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.

test the relationship between farmer willingness to pay for fertilizer and reported beliefs about fertilizer quality.

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.[20,21] One fertilizer and its corresponding bid was randomly chosen to be the binding round.[22,23]

Results from the BDM auction suggest that our belief elicitation measures concepts are relevant to farmers' willingness to pay for fertilizer.

Figure 2 shows the primary result graphically with a binscatter plot of the premium paid for tested fertilizer versus beliefs about fertilizer quality in the local market.[24] 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 fertilizer quality: Farmers who believe all fertilizer is good quality were willing to pay 26% more for local fertilizer than those who believe all fertilizer in the local market is bad quality. Correspondingly, the premium farmers are willing to pay for tested fertilizer is related to their beliefs about the quality of fertilizer in their local market. Farmers who believe that all fertilizer in their local market is bad quality are willing to

[20]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 bad 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.

[21]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.

[22]Compliance was high. Of those who won the auction, 97.5% agreed to pay the price drawn from the bag.

[23]75% of farmers reported that the BDM was "easy to understand," and enumerators reported that 71% of farmers "fully understood" the task.

[24]Online Appendix Table B.2 shows the full results of a regression of farmer willingness to pay on an indicator that the fertilizer was tested. 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 land owned, 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.

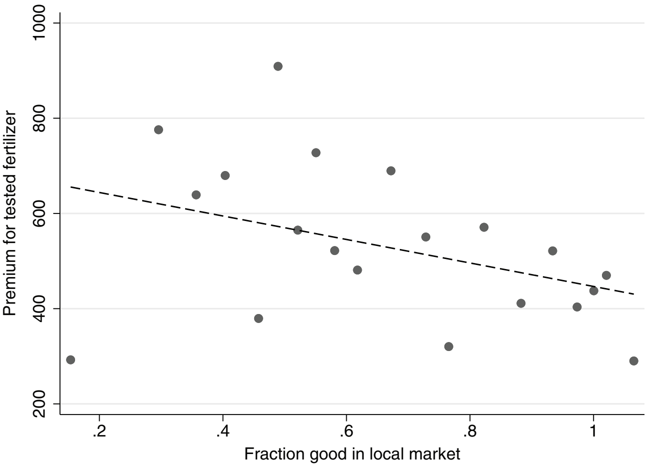

FIGURE 2 Binscatter of premium paid for tested fertilizer by beliefs about fertilizer quality. Figure shows the regression line and a binscatter plot of the premium farmers in Tanzania are willing to pay for fertilizer that has been tested and assured to be perfect quality relative to that farmer's beliefs about the fraction of fertilizer that is good quality in their local market.

pay a 62% premium for tested fertilizer, whereas those who believe that all fertilizer in their local market is good quality are willing to pay only 38% more for tested fertilizer.

3 | MODELING LEARNING WITH MISATTRIBUTION

We develop a learning model to reconcile two stylized facts: (1) farmers believe much of the fertilizer available to them is bad quality; (2) the fertilizer in the local area is in fact mostly good quality. In the main text we present the model intuition and fundamentals; we provide the mathematical details in Online Appendix A.

Previous models to explain incorrect beliefs generally fall into two categories: models based on misspecification and models based on rational inattention. Models based on misspecification assume that agents learn, but that they miss salient features of their experience. Farmers engaged in misspecified learning either do not know about the important factors of production, or they misunderstand how those factors interact to affect production. Models in this category have been applied to a range of contexts including firms, consumer behavior, and health (Arrow & Green, 1973; Esponda & Pouzo, 2021; Sobel, 1984; Spiegler, 2016). Models based on rational inattention assume that agents do know the important factors of production but have chosen to ignore some of those factors under the assumption that that factor does not affect production enough to justify the cost of obtaining information about it (Hanna et al., 2014; Maćkowiak et al., 2023; Schwartzstein, 2014; Sims, 2003). Both models of learning based on misspecificaton and rational inattention assume that the agent misunderstands some feature of the production function.

Our model takes a different approach. We assume that farmers know everything there is to know about the production function; that they understand it and observe its inputs perfectly. However, fundamental features of the production process cause farmers to *misinterpret* the signals that output realizations provide about input quality. If farmers attribute good outcomes to good-quality fertilizer and bad outcomes to bad-quality fertilizer, farmers who use good-quality fertilizer might mistakenly "misattribute" bad outcomes to have come from using bad-quality fertilizer.[25]

[2525]This is different than a farmer observing yields and forming their belief about fertilizer quality by asking themselves what the proportion of good-quality fertilizer must have been to maximize the likelihood they observed those yields. In that situation a one-parameter mixture model would be more appropriate, and the farmer's beliefs converge to the true proportion of good-quality fertilizer as they observe more yields. When all fertilizer is good quality, farmers do not think there is any bad-quality fertilizer. In contrast, our model explains how beliefs do not converge to the truth when there is no bad-quality fertilizer.

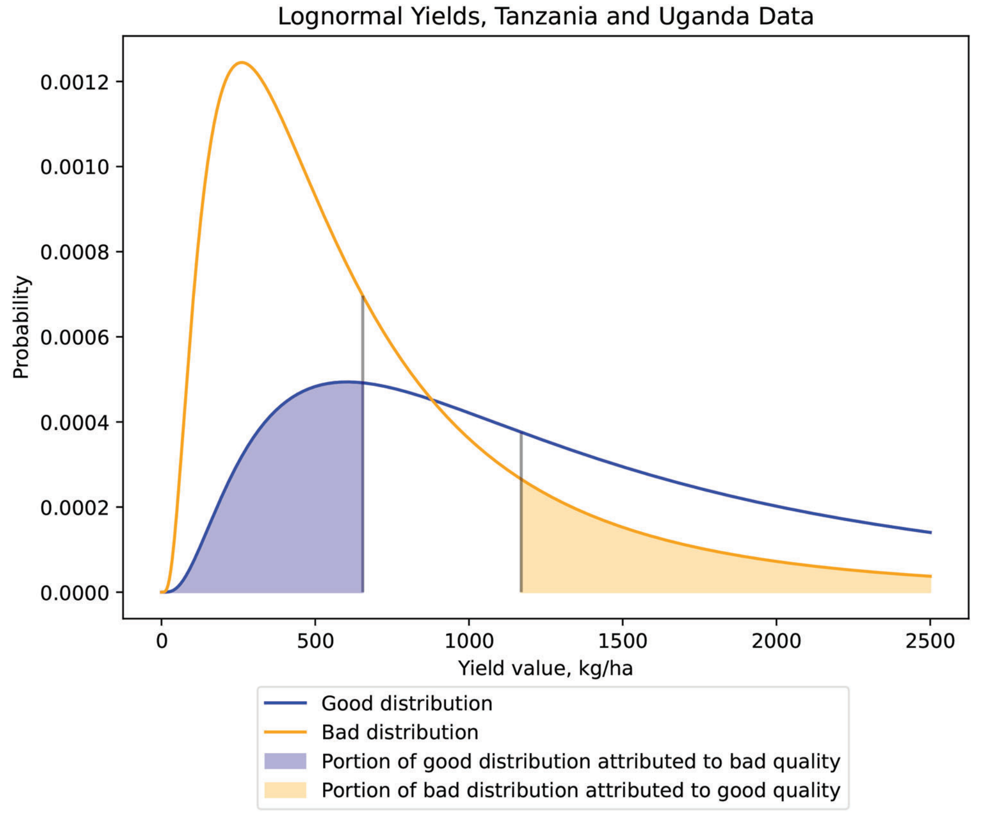

FIGURE 3 Misattribution. Figure shows the intuition behind misattribution. There are expected distributions of yields from using good-quality fertilizer and bad-quality fertilizer. When yield realizations are more likely to come from the good distribution than bad distribution, then the quality of fertilizer is attributed to be good. The reverse is true for attributing low yield realizations to come from using bad-quality fertilizer. These rules lead to truly good-quality fertilizer being misattributed as bad quality, which is the shaded blue region of the good-quality fertilizer distribution. Farmers might only infer quality if a yield is highly likely to come from one distribution over the other; this sense of caution causes a region of overlap in the distributions with similar likelihoods where the farmer does not try to infer quality from the yield. This is the unshaded region between the two vertical grey lines.

Figure 3 demonstrates the central feature of our model. The orange curve shows a log-normal distribution of expected maize yields using no fertilizer or bad-quality fertilizer.[26] The blue curve shows the distribution of expected yields using good-quality fertilizer. Suppose the farmer uses fertilizer and observes a yield of 2000 kg per hectare. This yield is easy to interpret, because the likelihood that this yield was drawn from the good-quality fertilizer distribution is much higher than the likelihood it was drawn from the bad-quality fertilizer distribution. Analogously, a yield of 250 kg per hectare is also easy for the farmer to interpret. The yield is much more likely to be drawn from the bad-quality fertilizer distribution than the good-quality. However, a yield of 800 kg per hectare is roughly as likely to have come from the good-quality fertilizer distribution as the bad-quality. It is not immediately clear what the farmer should conclude from this observation! This is the fundamental insight of our model: When the yield distributions are characterized by substantial overlap,

[26]We assume that bad-quality fertilizer has little nitrogen but is not deleterious to production. In our survey data from Tanzania, farmers believed plots with no fertilizer and with bad-quality fertilizer would produce 834 and 778 kilograms of dried, shelled maize per hectare, respectively; the difference is not statistically significant at the 5% level. Because we model the farmer using fertilizer in every period, we refer to this distribution as coming from bad-quality fertilizer.

farmers will find it difficult to deduce whether some yield observations were drawn from the good-quality or bad-quality fertilizer distribution.

Knowing that misattribution is possible, farmers could choose some range of yields for which they decide that it is neither possible nor prudent to draw any conclusion at all. We parameterize this choice with a caution parameter, γ. In the figure, γ relates to the width of the middle range between the gray vertical lines where the yield curves are so close to one another that no conclusion is drawn. Beyond some threshold, the farmer concludes that the yield is high enough that the fertilizer is more likely good quality than bad quality. Similarly, beneath some threshold the farmer concludes that the yield is low enough that bad-quality fertilizer is more likely than good quality. However, given substantial overlap between the distributions, misattribution is common. The area shaded in blue represents the region in which a farmer concludes that the yield they observed is so low that the fertilizer they used must be bad quality, but in fact the fertilizer they used was good quality and they got unlucky in application, seed quality, the timing of rainfall, temperature, not using the correct type of fertilizer, or some other factor that affected production. This is analogous to a Type I error. The area shaded in orange represents the region in which a farmer concludes that their yield was so high that the fertilizer they used must be good quality, but in fact the fertilizer they used was bad quality and they just had a lucky season. This is analogous to a Type II error. Note that in our context, most or all fertilizer is actually good quality, so farmers applying fertilizer are in fact only drawing from the blue distribution; positive misattribution—Type II errors—do not occur.

Notice the unavoidable trade-off between accurate inference and any inference at all. Aware that the yield distributions overlap, the farmer may attempt to reduce misattribution by being more cautious in drawing conclusions from yields. The middle region of the figure from which they draw no inference then expands. This will reduce their incidence of incorrectly concluding that good-quality fertilizer was bad quality (i.e., reducing the area shaded in blue in the figure), but it will also necessarily reduce the number of yield draws from which the farmer draws any information at all. This allows incorrect beliefs to persist, as they are not updated in response to previously informative yields that are now deemed uninformative.

Farmers can understand the production process perfectly and completely—but still, they face a trade-off between drawing incorrect conclusions or making no conclusion at all. Our framing has implications for policy: Programs intended to improve farmer understanding of the production process might not affect beliefs. Farmers' beliefs about fertilizer quality are unlikely to be improved through their own observations; the only way to circumvent misattribution is through a trusted regulatory process to ensure quality or strong signals about quality in markets.

In Online Appendix A we provide the mathematical details of the model. In short, we assume favorable conditions for learning: Farmers are Bayesian updaters, they have a correct understanding of the yield distributions using either good-quality or bad-quality fertilizer, and farmers use fertilizer continuously for 50 periods;[27] although we describe a farmer observing only their own single plot, the model is agnostic to the source of observations so one could imagine the farmer observing multiple plots or basic social learning instead (see Online Appendix A). Even under these favorable assumptions, our model simulations show that learning about fertilizer quality is persistently inhibited when misattribution is present.

3.1 | Simulation results

To explore the implications of our model for farmer learning over time, we simulate how a farmer's beliefs change when they observe yields over many periods. We then vary how cautious the farmer is

[27]This assumption is clearly inconsistent with observational data. In our samples, more than two-thirds of farmers report never having purchased fertilizer. Lack of experience with fertilizer will slow learning. We assume continuous fertilizer use because it provides strong conditions for learning. Our results show that learning is still extremely difficult, even under these generous assumptions.

to show that misattribution leads to a trade-off between incorrect learning and any learning at all. When farmers draw inferences more cautiously, there is less misattribution of bad yields to bad-quality fertilizer but also less frequent belief updating. In Figure 6 and in Figure B.2 in Online Appendix B, we present simulations using yield distributions that are more and less favorable to inference in our model. When the distribution of yields from good-quality fertilizer are significantly higher than that from bad-quality fertilizer, it becomes easier to infer fertilizer quality from yield observations (Figure 6); when the yield distributions are more overlapping, inference is more difficult (Figure B.2). This connection between the relative shape and scale of the distributions of yields from good- and bad-quality fertilizer and the resulting beliefs about fertilizer quality suggest that the problem of misattribution is driven by the production technology linking inputs to outputs.

The key insight from the model is that if farmers' expected yield distributions with good- and bad-quality fertilizer overlap, learning about true (good) quality is difficult. We assume that farmers have some distributions in mind, but we do not know what those distributions are. Farmers may condition their expectations on weather, labor inputs, or other exogenous or endogenous factors of production. Our simulations use unconditional distributions of yields (which likely have more variance than conditional distributions) but rely on the optimistic learning assumptions and circumstances in the model. Our simulation results therefore are unlikely to be either a best- or a worse-case scenario for learning but lie somewhere in between.

As the farmer infers good or bad quality from a single informative yield, we think of the inferred quality as a Bernoulli process; good quality is a success, and bad quality is a failure. This leads us to use a binomial distribution to model the series of inferred fertilizer qualities. We model the farmer's beliefs using a beta distribution, the conjugate prior of the binomial, 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 parameters, α and β, where $\alpha-1$ indicates the number of former successes observed and $\beta-1$ indicates the number of former failures. The beta distribution we use for an initial prior is set to $\alpha=\beta=1$ and is identical to the uniform distribution.[28]

The simulation requires us to specify several parameter values: the number of time periods over which the farmer learns,[29] the distributions of expected yields using good- and bad-quality fertilizer, the true distribution from which yields are drawn, and the caution parameter.

The simulation proceeds as follows:

1. Set the parameter values of the yield distribution using good-quality fertilizer, $f(y|g)$, the yield distribution using bad-quality fertilizer, $f(y|b)$, and the true yield distribution, $f(y)$.
2. Seed the initial prior belief, $p_0=\text{Beta}(\alpha_0,\beta_0)=\text{Beta}(1,1)$, the uniform distribution.
3. Set the caution parameter γ that governs the percent of yields deemed informative.
4. For each time period $t\in\{1,T\}$,
   a. Draw a yield y_t from the true yield distribution.
   b. Compare $f(y_t|g)$ to $f(y_t|b)$. If $\frac{f(y_t|g)}{f(y_t|b)}>\gamma$, conclude that the fertilizer was good quality; if $\frac{f(y_t|b)}{f(y_t|g)}>\gamma$, conclude that the fertilizer was bad quality; otherwise, conclude that the yield was uninformative.
   c. Update the α_t and β_t parameters of the belief 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, and $\alpha_{t+1}=\alpha_t$ and $\beta_{t+1}=\beta_t$ if yield was categorized as uninformative.
   d. Form p_{t+1} and repeat at (a).

[28]The uniform distribution is commonly used as the initial prior when the agent has no clear initial belief. This practice dates back to Bayes and Laplace (Gelman et al., 2014). We have also run simulations with priors set to distributions centered on 0.1, 0.2, … 0.8, or 0.9 to see how beliefs evolve when an agent begins with pessimistic or optimistic beliefs. The resulting patterns in posteriors are nearly identical to those shown here (available on request).

[29]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.

TABLE 4 Simulation parameters, values, and sources.

Input	Purpose	Baseline value	Source
T	Number of periods	50	25 years of growing seasons
Prior	Starting beliefs about rate of good quality fertilizer	Beta distribution with $\alpha = \beta = 1$	Parameter values for a uniform distribution; akin to an uninformative prior
$f(y\|g)$	Expected yield distribution using good fertilizer	$\text{Lognormal}\left(2012, \left(\frac{272}{245} * 2012\right)^2\right)$	Tanzania yield expectations and Uganda realized yield variances
$f(y\|b)$	Expected yield distribution using bad fertilizer	$\text{Lognormal}\left(778, \left(\frac{266}{257} * 778\right)^2\right)$	Tanzania yield expectations and Uganda realized yield variances
$f(y)$	Distribution from which yields are drawn	$\text{Lognormal}\left(2012, \left(\frac{272}{245} * 2012\right)^2\right)$	Tanzania yield expectations and Uganda realized yield variances
γ	Caution parameter: governs willingness to consider yield informative about quality	1.42	75% of yields informative

Note: Table shows, for each input in a simulation, its purpose, baseline value, and source for the value.

Table 4 presents the values for each parameter of our baseline simulations. For each specification we set the number of periods to 50; given that Tanzania and Uganda, like many other countries in the region, have two production seasons per year, 50 periods can be thought of as representing 25 years of growing seasons in East Africa. The initial prior is parameterized to be the uniform distribution, with $\alpha = 1$ and $\beta = 1$. The expected distribution of yields using good-quality fertilizer is set toLognormal $\left(2012, \left(\frac{272}{245} \times 2012\right)^2\right)$. We set the mean of this distribution to the mean yield expected by the Tanzanian farmers in our data set when using good-quality fertilizer. We set the variance of the good-quality yield distribution to match the relative variance of realized yields to their mean as reported in our Ugandan data.[30] The expected distribution of yields using bad-quality fertilizer is set toLognormal $\left(778, \left(\frac{266}{257} \times 778\right)^2\right)$, with the mean yield set to be what Tanzanian farmers expected when using bad-quality fertilizer and the variance scaled to match realized Ugandan maize yields from farmers who did not use fertilizer.[31] We assume that the true fraction of good-quality fertilizer is 1, and true yields are drawn fromLognormal $\left(2012, \left(\frac{272}{245} \times 2012\right)^2\right)$ because nearly all fertilizer in the region has been found to be good quality; thus, if beliefs were accurate, the mean of p_t would converge to 1. In Figure 4 we present beliefs with γ set so that 100%, 75%, 50%, 25%, and 10% of yields are informative; thereafter we present results with γ set so that 75% of yields are deemed informative given other parameter values. In the following figures, we present the mean of the beta belief distribution in each period. Each time we run a simulation, the statistics of interest vary due to the stochasticity in the model, so we run each simulation 1000 times and average over them.

Figure 4 presents the results of our baseline simulation, with beliefs shown on the y-axis and the number of time periods on the x-axis. The dashed black line shows how beliefs evolve when there is

[30]We did not ask the Tanzanian farmers in our survey to report their expected variance of yields because we were worried that the data would not be good quality. We recognize that using variances from one data source and means from another is not ideal. In Online Appendix B, we show simulations using both means and variances from realized yields in the Uganda data in Figure B.3. The misattribution problem in that scenario is worse because yields are actually lower on average for the farmers who used fertilizer, shown in the Online Appendix in Figure B.2. This relationship between fertilizer use and low yields should not be considered causal, however, because fertilizer use is endogenous to numerous other farmer practices and farm conditions. Additionally, the Uganda data report realized yields, whereas the model focuses on expected yields that may be different from actual realizations. For these reasons, we present simulations using mean expectations from the Tanzanian data and variances from the realized yields in Uganda in the main text, while also providing simulations with alternate parameter choices in the Online Appendix.

[31]We do not have data on yield realizations using bad-quality fertilizer, but farmers' expectations from using no fertilizer and bad-quality fertilizer are statistically indistinguishable, so we assume the variance of yields using no fertilizer are a stand-in for the variance of yields using bad-quality fertilizer.

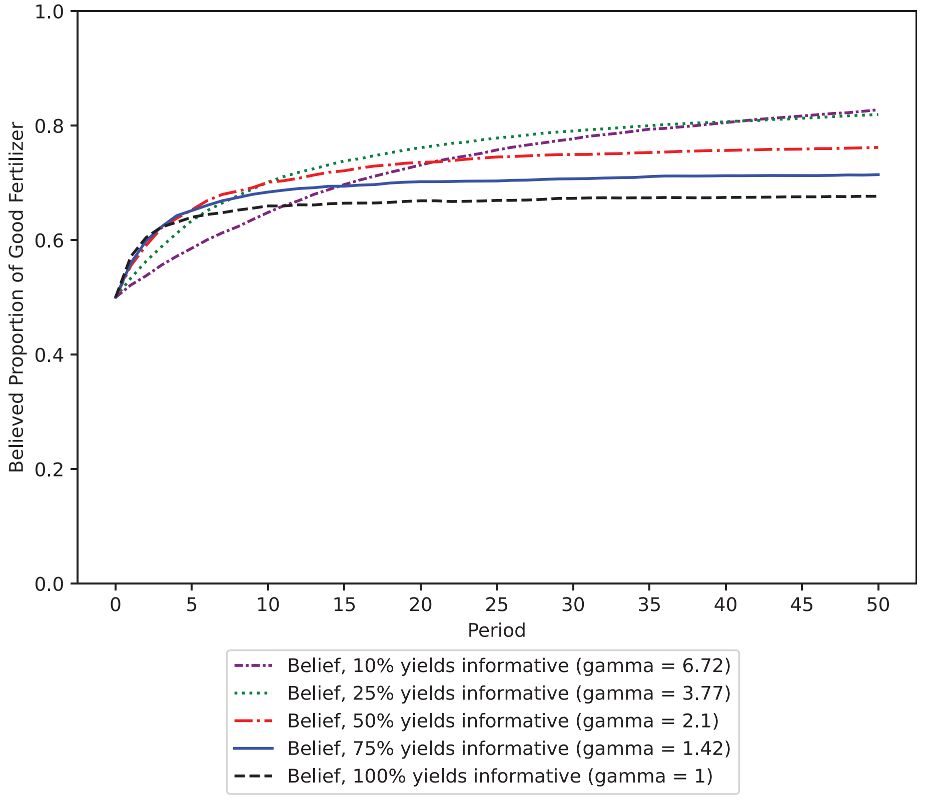

FIGURE 4 Evolution of beliefs with misattribution. The figure shows simulations of the belief updating model over 50 periods with yield distributions calibrated to what Tanzanian farmers say they expect from using the good-quality and bad-quality fertilizer. The five lines on the plot show the evolution of beliefs when 100%, 75%, 50%, 25%, and 10% of yields are deemed informative.

no caution and all yields are deemed informative. The solid blue line shows beliefs when farmers are cautious about misattribution, and only 75% of yields are deemed informative. The remaining three lines show how beliefs evolve when the farmer is increasingly cautious; the red line corresponds to 50% of yields deemed informative, the green to 25% of yields deemed informative, and finally the purple line shows how beliefs evolve when only 10% of yields are deemed informative.

The black dashed line shows that when all yield observations are deemed informative, beliefs improve initially, but they converge to a level that is far from the true proportion of good-quality fertilizer in the market: 1. This occurs because when the farmer observes a poor yield, they sometimes attribute it to bad-quality fertilizer rather than an unlucky season. Conditional on an amount of caution, the farmer's beliefs about fertilizer quality are isomorphic to the degree of overlap between the good- and bad-quality fertilizer distributions. As the amount of overlap increases, the farmer's beliefs become worse. The solid blue line shows that when the farmer is aware that they may misattribute an unlucky yield draw to bad-quality fertilizer and exercises caution in interpreting yields so that only 75% are deemed informative, beliefs do converge to a higher, more accurate level. When the proportion of yields deemed informative decreases to 50%, 25%, and then 10%, beliefs increase further still. However, beliefs remain far from the truth, even after 50 periods.

What if the farmer were even more cautious? Figure B.5 in Online Appendix B hows that additional caution cannot solve the misattribution problem. The figure presents the mean belief after 50 periods on the y-axis while varying the caution parameter, γ, on the x-axis. The figure starts with all yields being deemed informative ($\gamma = 1$) and ends with so much caution that less than 0.001% of

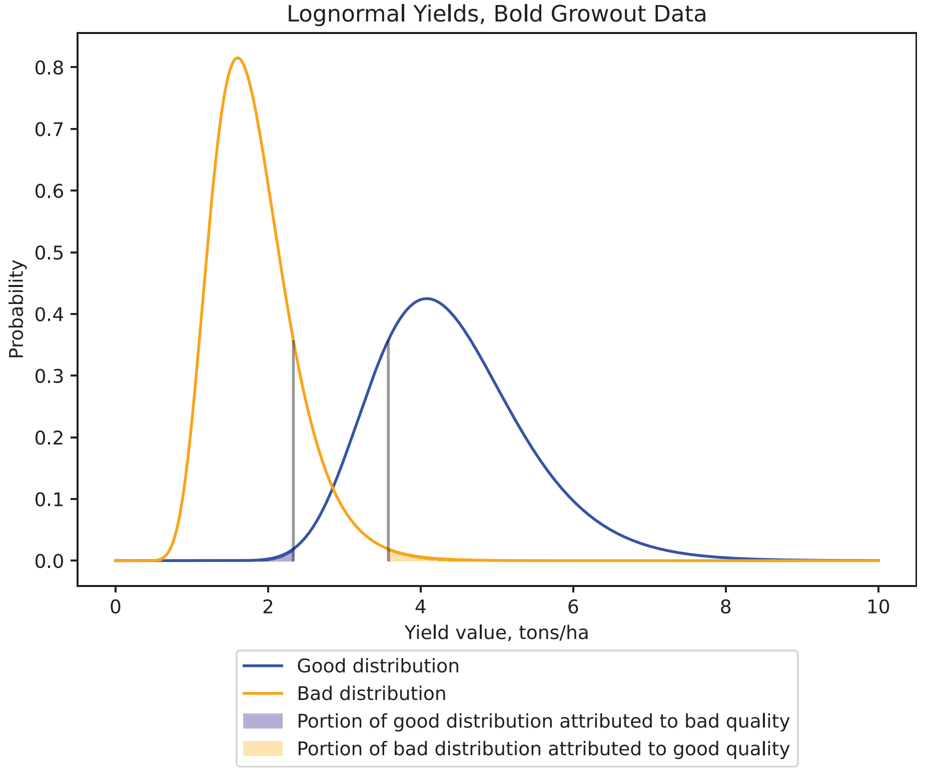

FIGURE 5 Misattribution with grow-out trial yields. Figure shows the regions of misattribution when the farmer's believed yields and true yields come from grow-out trial data. Data comes from Bold et al. (2017) grow-out trials. Yields from good-quality fertilizer are much higher than bad-quality fertilizer and there is little overlap in the two distributions of yields.

yields are deemed informative ($\gamma = 50$). Beliefs do improve when farmers are more cautious about interpreting yield observations, but eventually too much caution causes farmers to discard too many observations, limiting their ability to learn and keeping final beliefs close their initial prior of 0.5.[32]

Our choices for the mean yield parameters for the baseline simulations are based on Tanzanian farmers' reported yield expectations using good-quality (2012 kg of maize per hectare) and bad-quality (778 kgs per hectare) fertilizer. However, yields are often considerably more distinct when fields are tended by professional agronomists. In the grow-out trials cited in Bold et al. (2017) in Uganda, the difference between yields with good-quality fertilizer (4400 kg per hectare in the grow-out trial) and no fertilizer (1820 kg per hectare) was substantially larger than our Tanzanian farmers' expectations. The yield distributions using this data are shown in Figure 5. Might learning improve if farmers expected and observed yields more in line with grow-out trials?

Figure 6 shows simulations that are seeded with yield data from the Bold et al. (2017) grow-out trials rather than farmers' reported yield expectations. This in essence shows simulations of learning under the very best possible circumstances, with a wider distance between the good-quality and bad-quality fertilizer yield distributions. 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 the belief that all fertilizer is good quality. This occurs because when the yield distributions using good- and bad-quality fertilizer overlap at all, there will always be scope for misattribution.

[32]Figure B.4 in Online Appendix B suggests that beliefs do not converge to the truth in the long run in the presence of misattribution; after 1000 periods of learning, beliefs do not improve much beyond just 50 periods of learning.

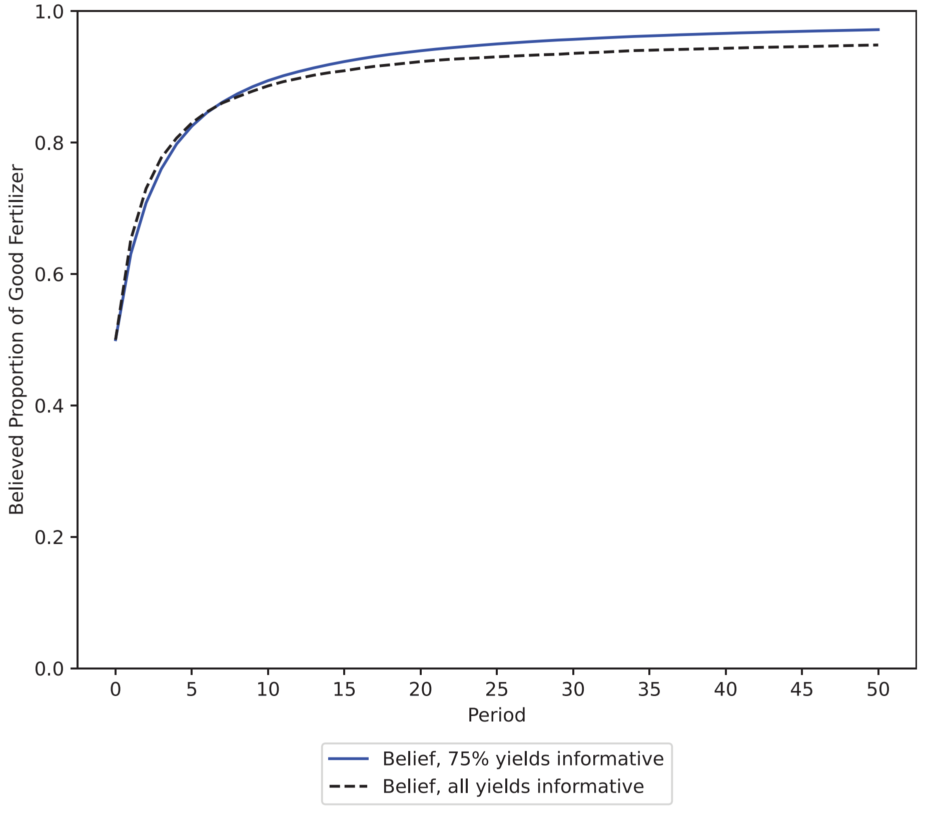

FIGURE 6 Evolution of beliefs with misattribution with yields from grow-out trials. The figure presents the results of simulations of the belief updating model over 50 periods with yield distributions calibrated to the yield distributions from the Bold et al. (2017) grow-out trials in Uganda. The dashed black line shows how beliefs evolve when there is no caution and all yields are deemed informative. The solid blue line shows beliefs when farmers are cautious about misattribution and only 75% of yields are deemed informative.

In summary, our belief updating model and its simulations show that when farmers begin with no clear idea about the true ratio of good- and bad-quality fertilizer in the market and observe yields consistent with those obtained by professional agronomists in grow-out trials for 50 periods, their beliefs still do not fully converge to the truth that all of the fertilizer in their local market is good quality.

3.2 | 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—and therefore more variable yields—will be more likely to experience a negative production shock that they misattribute to bad-quality fertilizer. Results of our model and simulations imply that these farmers will hold beliefs that are more incorrect on average.

Implicit in this exercise is the assumption that more variable rainfall is associated with more variable maize yields. Research at the intersection of climate science and agronomy has demonstrated that weather variability contributes significantly to yield variability (Chen et al., 2013; Ortiz-Bobea et al., 2021; Osborne & Wheeler, 2013)—with weather variability explaining sizeable but

TABLE 5 Relationship between precipitation variation and beliefs about fertilizer quality in Uganda.

Variables	(1) Mean belief
Historic variance in precipitation: First season	−0.26*** (0.09)
Farmer age	0.00 (0.00)
Farmer male	0.02 (0.02)
Farmer is household head	0.01 (0.02)
Farmer has not completed primary school	0.00 (0.02)
Household size	0.00 (0.00)
Acres owned	0.01*** (0.00)
Ever used fertilizer	0.04** (0.02)
Constant	0.63*** (0.04)
Observations	1346
R-squared	0.03

Note: The table presents the relationship between mean belief about the fraction of fertilizer that is good quality in the local market and historic rainfall variation in Uganda. The regression includes demographic controls for 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 are also included and comprise whether the farmer has ever used inorganic fertilizer and the number of acres owned.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

heterogeneous shares of variation in yields depending on the region and crop.[33] Ray et al. (2015) focus on variation in maize yields driven by variation in precipitation in parts of Sub-Saharan Africa and characterizes the relationship between maize yield variability and rainfall variability in the region (p. 6), "Overall, precipitation variability is more important in sub-Saharan Africa, pointing to the predominantly rainfed system of maize cultivation." They note that their finding that precipitation variability is of particular importance to maize yield variance in the region is consistent with previous work including Koo and Cox (2014) and Phillips et al. (1998) among others. To the extent that yield variation is driven by precipitation variability, our model suggests that regions with more variable rainfall will have worse beliefs.

We use the Uganda data set and daily precipitation data from the Climate Hazards Group Infra-Red Precipitation with Station (CHIRPS) data set (Funk et al., 2015) to test the implications of our model and simulations. 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.[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 in 2013). We focus on precipitation variation in the first season, but results are robust to including both growing seasons. Figure B.6 in Online Appendix B shows the geographic distribution of households in the Uganda sample.

Table 5 shows the results of a regression of farmers' mean beliefs about fertilizer quality on the historical variance in precipitation in the first growing season, as well as demographic and farming

[33]Ray et al. (2015) for example find that weather variability explains 30% of the variability in crop yields in their global analysis whereas Vogel et al. (2019) suggest the figure might be as high as 43%.
[34]Results are robust to 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 might be easily attributable to nonfertilizer causes and not used when inferring fertilizer quality. Robustness tables are shown in Online Appendix B.

controls.[35] We cluster standard errors at the village level. The estimating equation is shown below as Equation (1). The results show that beliefs are highly correlated with weather variability.[36]

$$\text{Belief}_{iv} = \beta_0 + \beta_1 \text{RainfallVariation}_{iv} + \beta_2 \text{Demographics}_i + \beta_3 \text{FarmingVars}_i + \varepsilon_{iv} \tag{1}$$

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, the results are consistent with the hypothesis that rainfall variability makes misattribution more likely, which makes learning more difficult.

4 | CONCLUSION

Consumers can have trouble learning about a product's quality or efficacy. In this paper we show that misattribution can inhibit learning about quality. When the process that converts inputs to outputs is noisy, and the distribution of outcomes using a good-quality input overlaps with the outcomes using a bad-quality input, individuals may mistakenly attribute a bad outcome to the quality of the input when the bad outcome was actually caused by natural variation or bad luck. We call this phenomenon misattribution. We incorporate misattribution into a model of learning about product quality. Our model simulations show that when misattribution is present, beliefs may never converge to the truth even after observing many new data points. Our model and its conclusions are relevant to circumstances in which an agent cannot be immediately sure of a product's quality.

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 data set in Uganda, and precipitation data from Uganda to motivate the model and test its implications. We document that farmers report considerable 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, whereas 84% of farmers in Uganda have suspicions about quality. Results from the willingness-to-pay experiment show that farmers who report less optimistic beliefs about fertilizer quality in their local market are willing to pay less for local fertilizer and a larger premium for tested fertilizer. Farmers are willing to pay a premium for quality-certified fertilizer presumably because they believe much fertilizer in their local market is bad quality; this is a puzzle because urea fertilizer in the area has been shown to be reliably of good quality. Our model predicts that farmers who experience poor yields more often should have worse beliefs because they are likely to misattribute bad yields to bad-quality fertilizer more often. We use historic rainfall variability in Uganda to show an important association implied by the model: farmers who live in regions with greater precipitation variation have more incorrect beliefs about fertilizer quality than farmers who live in regions with more consistent rainfall.

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 inhibited by misattribution, fertilizer (and other similar goods) should instead be treated as a credence good—a good whose quality cannot be learned through use. Beliefs about fertilizer quality must be influenced by something other

[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.

[36]Table B.3 in Online Appendix B shows results for farmers who have used fertilizer in the past, those who have not, and an interacted model to show the difference in the effect of rainfall between these groups. The results show that rainfall is more tightly correlated with beliefs about fertilizer quality for those who have used fertilizer in the past, but the difference in the relationship between those who have and have not used fertilizer in the past is not statistically significant. We note however that the test of differences between those who have and have not used fertilizer in the past is underpowered. Rainfall variation is defined at the village level, and we have only 239 villages in our sample. Further, only 15% of farmers in our Uganda sample have ever used fertilizer, and some of those have used fertilizer in only one growing season. We therefore prefer to focus on the full sample of farmers in Uganda, regardless of previous fertilizer use.

than use. Other credence goods of this type include agricultural inputs such as seed and herbicides, but also medication, medical treatments, 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 they misattribute the poor outcome to a bad policy rather than bad luck.[37] In some sense, our results highlight the value of a strong and trusted scientific community and regulatory system, and illustrate what happens when trust and regulation breaks down.

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, and adverse events are detected via surveillance systems. The quality of education, for example, is certified by bodies at the state and national levels. When government certification is not available, crowdsourced verification tends to emerge through services such as Google and Yelp reviews. These services sometimes emerge to complement existing government assessments or to assess dimensions of product quality not covered by official means. By contrast, in low-income countries and communities, government and social-media-based regulatory systems often fail to function well, which is one reason why markets like the one for fertilizer in East Africa break down. Our work speaks to the breadth of value created by strong and trusted regulatory and verification systems.

Our results have three implications for programs designed to increase use of agricultural inputs and practices. First, our work suggests that programs that provide input subsidies or relax credit constraints for fertilizer and similar products may not on their own be enough to 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 a fertilizer and improved maize seed subsidy program in Mozambique showed that targeted farmers increased their usage of fertilizer and improved their beliefs about the efficacy of the input package in the year following the subsidy, but the effects showed some indication of waning in the second year after the subsidy (Carter et al., 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 are likely to attribute the high yields to high quality and/or 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, fertilizer and other agricultural inputs are not experience goods, so a few uses may not be enough to convince a user of their value.

Second, our results suggest an agricultural extension approach might be designed to highlight that the production process is stochastic—that soil, genetic varietals, environmental factors, and application technique all contribute to crop yields in addition to fertilizer (or seed) quality—and that one must be deliberate to distinguish them and to not misattribute. Extension agents might work to convince farmers that a single bad outcome may be indicative of bad luck rather than a bad-quality input. For example, they could implement realistic trial plots showing performance of new products under varying local growing conditions. This would effectively increase the caution parameter of our model, γ, which we showed does reduce the incidence of misattribution. However, our model and its simulations show limited scope for increased caution to improve beliefs because when cautious agents decide many observations are uninformative about product quality, they have no information to use to update their prior beliefs. If those cautious agents began with incorrect and pessimistic beliefs, those beliefs will persist.

Finally, an agricultural program that may have more success is a quality assurance plan that regulates and certifies product quality. 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

[37] We thank Kira Lancker for this example.

and guaranteed to be good quality than for fertilizer from their local market of unverified nutrient content. Michelson, Gourlay, et al. (2023) and Michelson, Magomba, and Maertens (2023) 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 improvements in farmers' beliefs about fertilizer quality and also that farmers purchased and used fertilizer more often.

Even so, it is important to consider the costs and total effect of quality certification programs on input use. Certification programs add costs that are likely to be passed on as increased prices for farmers. Moreover, verification will only work if farmers trust the verification and accurately update their beliefs. Information does not always lead individuals to update priors toward the truth (a point borne out in our theory and simulations).[38] A policy that increased costs without necessarily reducing or resolving uncertainty about product quality could further impede fertilizer use. Also, although the program in Uganda seems to have had lasting effects, the risk remains that the effectiveness of the verification program may fade over time. Because misattribution remains an issue, any certification system will remain vulnerable to a loss of trust.

Of course, not all farmers have incorrect beliefs about fertilizer quality. Because our work suggests that beliefs about credence goods will not fully update with use, it is important to understand how consumers form beliefs about new products' quality in the first place. A better understanding of the heterogeneity across farmers and the spatial patterns in beliefs within and across villages could provide insight into how to introduce new credence goods to the market.

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