AMBIGUITY AND CREDENCE QUALITY:
IMPLICATIONS FOR TECHNOLOGY ADOPTION

BY

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THESIS

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Abstract

Use of fertilizer and hybrid seed remains low in much of Sub-Saharan Africa. A possible contributor to low adoption is that farmers are uncertain about the quality of agricultural inputs available to them. While previous studies have shown that risk and uncertainty preferences are relevant to the decision to adopt a technology, existing research assumes that farmers have homogeneous beliefs about the quality of available inputs. I test this assumption using an incentivized Becker-DeGroot-Marschack auction in Tanzania and examine how farmer beliefs about mineral fertilizer quality in local markets influence their willingness-to-pay. I find that farmers are willing to pay 46% more for fertilizer that was laboratory tested and found to be pure than for untested fertilizer. Farmers who believe that more of the fertilizer for sale in their local market is low in quality are willing to pay a higher premium for laboratory-tested pure quality fertilizer, compared to untested fertilizer. Yet these results present something of a puzzle, given that three rounds of testing of fertilizer for sale in regional markets over five years have demonstrated that the nutrient content of fertilizer for sale in these contexts is consistently at or near advertised levels. Farmers appear to believe that low-quality fertilizer is far more prevalent in proximate markets than it actually is. How have farmers' incorrect beliefs persisted in equilibrium? I posit two interconnected mechanisms. First, misattribution: Yields are stochastic due to weather and other factors, and when a yield in a particular year is unusually low, farmers misattribute noise as indicative of low-quality fertilizer. Second, farmers experience both risk (uncertainty about whether a bag of fertilizer is bad) and ambiguity (uncertainty about the likelihood a bag of fertilizer is bad), and thus hold multiple priors. I develop a Bayesian learning model that incorporates both misattribution and multiple priors and show that in equilibrium beliefs do not converge to the truth. Supporting the model's findings, I use farmer survey data from Uganda to establish that historic precipitation variability relates to farmers' fertilizer quality belief distributions. I use the learning model to simulate several policy interventions, and show that subsidies, information campaigns, and plot-specific fertilizer recommendations improve beliefs, but do not cause beliefs to fully converge to the truth. Instead, policy makers should consider programs that address the misattribution problem.

To my mom and dad

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Table of Contents

Chapter 1

Introduction

The use of modern agricultural inputs in Sub-Saharan Africa is extremely important to increase crop yields, decrease poverty, and improve food security (Wortmann et al., 2017). Though recommendations based on agronomic and economic evidence consistently promote fertilizer and hybrid seed use, actual usage rates remain far below benchmarks for achieving these improvements (Duflo, Kremer, & Robinson, 2008; Suri, 2011; Beaman, Karlan, Thuysbaert, & Udry, 2013). Several hypotheses have been proposed for this chronic under-usage, including lack of knowledge among farmers about rates of return and proper usage, unavailability, credit constraints, and intra-household frictions (Feder, Just, & Zilberman, 1985; Foster & Rosenzweig, 1995, 2010; Jack, 2013).

Several recent studies have explored the possibility that various sorts of uncertainty influence adoption decisions. If farmers cannot be sure that a given input will improve their production, they may be less likely to adopt that input. Some studies have found that risk averse farmers are less likely to adopt new technologies (Liu, 2012; Liu & Huang, 2013) and others find evidence that ambiguity aversion is a barrier to adoption (Engle-Warnick, Escobal, & Laszlo, 2007, 2011; Ross, Santos, & Capon, 2012; Barham, Chavas, Fitz, Salas, &

Schechter, 2014; Elabed & Carter, 2015; Ward & Singh, 2015; Kala, 2019). Previous work focuses on the role of preferences in the adoption decision by implicitly or explicitly assuming that farmers hold essentially the same information sets; in other words, if farmers share certain beliefs about opportunities and risks, then different individual decisions must reflect different preferences. Nonetheless, in circumstances where uncertainty is high, these individual decisions are influenced by both preferences and beliefs (Manski, 2004).

In this paper I examine how farmer beliefs about agricultural input quality impact their demand for that input. I run a Becker-DeGroot-Marschak (BDM) auction with smallholder farmers in Tanzania to identify how farmer beliefs about mineral fertilizer quality in nearby markets influence their willingness-to-pay (WTP) for local mineral fertilizer and for lab-tested, pure quality mineral fertilizer (Becker, Degroot, & Marschak, 1964). I find that farmers' beliefs about mineral fertilizer quality in these markets do not reflect the actual fertilizer quality. Moreover, beliefs have major effects on farmer demand for fertilizer. I explain the persistence of these incorrect beliefs using a model of a farmer learning that accounts for (1) the possibility that a farmer misattributes bad yields to bad fertilizer and (2) the ambiguity a farmer faces in evaluation of input quality.

My analysis provides a critical step in understanding the problem of low adoption of modern inputs among smallholder farmers. Having documented that farmers' beliefs about input quality have large effects on their demand for those inputs, my study identifies features of agricultural systems that cause incorrect beliefs about input quality to persist, namely: use of incorrect inputs, misuse of correct inputs, and markets and information campaigns advertising unrealistically large effects of inputs.

My findings contribute to the literature on technology adoption and beliefs in the context of development. One line of research has shown that farmers do hold heterogeneous beliefs about agricultural markets and processes (Lybbert, Barrett, McPeak, & Luseno, 2007; Bellemare, 2009a, 2009b, 2012), and others have shown that beliefs influence farmers' agricultural decisions (Hill, 2009; Dillon, 2012; Giné, Townsend, & Vickery, 2017; Maertens, 2017). A second area of research has documented that individuals can hold incorrect beliefs about new products and agricultural processes in low-income countries. Björkman-Nyqvist, Svensson, and Yanagizawa-Drott (2020) and Adhvaryu (2014) find that biomedical misconceptions about malaria in Uganda and misdiagnosis of malaria in Tanzania, respectively, can inhibit consumer learning about the actual efficacy of antimalarial medicines. Hanna, Mullainathan, and Schwartzstein (2014) document that experienced farmers in Indonesia can fail to consider important features of the information they receive each season about how their input choices affect their yields and therefore make sub-optimal farming decisions. My paper bridges a gap between development literature on the origins and persistence of incorrect beliefs and research focused on how farmer beliefs affect technology adoption. Specifically, I find that farmers are willing to pay 46% more for lab-tested, pure urea fertilizer over local urea, but that this premium nearly disappears if a farmer correctly believes that all their local fertilizer is of good-quality.

I add two important features to models of agricultural learning in low-income countries. First, I acknowledge the ambiguity present in the environment in which a farmer learns by explicitly modeling the farmer updating multiple priors instead of a single prior. Second, I incorporate how farmers can treat an input as an experience good when it actually is a credence good, leading to incorrect beliefs about the input's quality through misattribution, whereby the farmer infers the quality of the input by looking at the outcome of an entire agricultural cycle.

A farmer faces ambiguity when the actual probability of uncertain outcomes is unknown to her. Research on agricultural decision making has found that ambiguity aversion impedes adoption (Engle-Warnick et al., 2007, 2011; Ross et al., 2012; Barham et al., 2014; Elabed & Carter, 2015; Ward & Singh, 2015; Bryan, 2019). However, most research on farmer learning in low-income countries has either ignored ambiguity in sources of information or has made an implicit assumption that individuals reduce all sources of information to a single prior. Models based on different learning mechanisms, from learning from others (Besley & Case, 1994; Foster & Rosenzweig, 1995; Munshi, 2004; Conley & Udry, 2010; Takahashi, Mano, & Otsuka, 2019) to individual learning (Hanna et al., 2014; Bold, Kaizzi, Svensson, & Yanagizawa-Drott, 2017; Gars & Ward, 2019), have generally not taken ambiguity into account. A notable exception is Kala (2019), who documented Indian farmers exhibiting ambiguity aversion when inferring optimal planting times from cumulative rainfall they experience. Kala (2019) found that farmers acted as if monsoon signals were drawn from one of multiple distributions and made planting decisions according to the worst-case distribution. My research differs in that I model each of the farmer's beliefs and I model farmers acting as in

Epstein and Schneider (2007), performing a likelihood ratio test for each of their beliefs against their single most likely belief and retaining and updating those which pass this test.

Belief formation and learning about input quality in a low-income country can be inhibited by multiple factors. It can be difficult to learn about many agricultural inputs (for example, improved seeds and fertilizer) because these products are both credence and experience goods (Darby & Karni, 1973) whose quality can be learned only through use, but because of their interactions with other inputs and stochasticity in crop-yield outcomes, their quality and relative importance often must be learned over a succession of crop cycles. Bold et al. (2017) argues that statistical noise can make it difficult for farmers in Uganda to learn about the quality of their fertilizer. Learning can also be inhibited by misunderstanding the data-generating processes creating informative signals (Adhvaryu, 2014; Hanna et al., 2014; Björkman-Nyqvist et al., 2020). Results from my qualitative work with farmers in Tanzania suggest that farmers are likely to misattribute poor crop yield to low-quality fertilizer when other factors may be at play. My learning model takes this misattribution into account when modeling the evolution of a farmer's beliefs over multiple seasons.

In Chapter 2 I describe smallholder agriculture Morogoro Region, Tanzania, relevant characteristics of farmers in my sample, and the experimental design. In Chapter 3 I report farmers' beliefs about fertilizer quality, present the results of the BDM auction, and explore how farmers' beliefs about fertilizer quality relate to their WTP for local, unknown quality urea fertilizer and lab-tested, pure urea fertilizer. In Chapter 4 I posit an explanation for incorrect farmer perceptions about mineral fertilizer quality, model a farmer with multiple prior beliefs who learns with misattribution about fertilizer quality, and compare the effects of different policies intended to increase input use by using the learning model to simulate their effects on the beliefs of a farmer. In Chapter 5 I discuss the findings of my study in the larger context of agricultural input adoption in low-income countries, and in Chapter 6 I conclude.

Chapter 2

Setting, Sample, and Experimental Design

2.1 Setting and Sample Description

My study takes place in the Morogoro Rural, Kilosa, and Mvomero districts in the Morogoro Region of Tanzania. Morogoro Region is in the mid-eastern part of the Tanzanian mainland, about 120 miles west of Dar es Salaam, Tanzania's largest city. Morogoro Region is a large producer of food crops, including maize, paddy rice, millet, and beans, and cash crops including cotton and tobacco (*Agriculture Sample Census Survey*, 2008). The region is marked by low mineral fertilizer use – only 13% of farmers reported using mineral fertilizer in the 2007-2008 agricultural growing season (*Agriculture Sample Census Survey*, 2008). The quality of mineral fertilizer is good, however: Morogoro Region is where Michelson, Fairbairn, Maertens, Ellison, and Manyong (2020) tested more than 800 samples of urea and diammonium phosphate (DAP) fertilizer from agricultural input shops throughout the region in 2015-2016 and found nearly all urea fertilizer samples to be of excellent quality (only two out of 300 urea samples were out of compliance with industry standards). Additionally, in advance of my own study I sampled and tested an additional 45 bags of urea fertilizer and found all met industry standards.

In June of 2019 I compiled a list of 18 rural villages reachable in one day's drive from Morogoro Town, the regional capital. Morogoro Town is a centrally located, urban city with large markets made up of many shops; there are at least six different agricultural input shops alone in Morogoro Town. I restricted the sample to villages around Morogoro Town because I wanted farmers in the study to have some knowledge about mineral fertilizer. Further, the field manager worked with local agricultural extension agents to invite twenty maize farmers from each village to participate in the study. Growing maize in Sub-Saharan Africa is amenable to mineral fertilizer (Kaizzi et al., 2012; Sime & Aune, 2014; Wortmann et al., 2017), so maize farmers were likely to have knowledge about fertilizer and its effects on their crops. I designed the sample so that half of the invited farmers consisted of women, reflecting the regional proportion of growers (*Agriculture Sample Census Survey*, 2008). My sample size is 348 farmers; in seventeen of the villages the research team interviewed twenty farmers while in one village we were only able to interview eight farmers.

Table 2.1 describes the demographic and farming characteristics of the farmers in the sample. Notably, the share of farmers in my sample who used mineral fertilizer in 2019 is 12%, close to the share reported in the 2007/08 Tanzania National Sample Census of Agriculture.

The average study participant age was 44 years old, and approximately two-thirds of the sample reported that he or she was the head of household, with household sizes of 3.88 people on average. Sampled farmers cultivate approximately three acres on average; all farmers grew maize, and the other crops were mostly paddy, sunflowers,

Table 2.1: Demographic and farming summary statistics of the farmers in the study sample

	(1)
	Mean and Standard Deviation
Age	44.43
	(13.09)
Male	0.49
	(0.50)
Household head	0.68
	(0.47)
Primary education	0.85
	(0.36)
Household size	3.88
	(2.11)
Acres cultivated in 2019	3.02
	(2.06)
Ever purchased fertilizer	0.34
	(0.48)
Ever purchased fertilizer in Morogoro	0.15
	(0.36)
Used mineral fertilizer in 2019	0.12
	(0.32)
Used organic fertilizer in 2019	0.09
	(0.28)
Observations	348

vegetables, and peas. Only a third of the sample had ever purchased fertilizer and only one sixth had bought fertilizer in Morogoro Town previously. Twelve percent of the sample used mineral fertilizer in 2019, and a tenth used organic (e.g., manure) fertilizer in 2019.

2.2 Survey Description

The survey was designed to measure the impacts of farmers' beliefs about fertilizer quality on their demand for fertilizers of different perceived qualities. Beliefs about fertilizer quality were elicited in one module, and demand for fertilizers of different perceived-quality was elicited through a real-stakes, Becker-DeGroot-Marschak (BDM) auction whereby the farmer bid for locally bought urea fertilizer, urea bought in Morogoro Town, and urea bought in Morogoro Town that was lab-tested (in labs in the United States) and found to be of pure quality. Even though only 34% of the sample had ever used fertilizer, all had heard about fertilizer from neighbors, extension agents, agro-dealers, and other sources of information, so had formed some sort of belief about its quality.

Care was taken in the design of the experiment to avoid recency and order effects. Being asked to provide their beliefs about fertilizer quality could affect a farmer's subsequent valuation of the different fertilizers due to recency effect of thinking about fertilizer quality in their local market or Morogoro Market. In addition, the order in which the three fertilizers was presented to the farmer could affect their bids through order effects; an order of locally bought urea fertilizer, then Morogoro Town bought urea fertilizer, then Morogoro Town bought, lab-tested pure urea fertilizer could send the implicit message that local fertilizer was the worst quality. A farmer might think that fertilizer from Morogoro is better than fertilizer from their local market because they know that Morogoro agro-dealers have higher thoughput than local agro-dealers so the fertilizer from Morogoro is likely to be newer, and that Morogoro agro-dealers might have more incentive and pressure from increased competition to provide good-quality inputs.To account for these two possible effects on a farmer's bids, farmers were randomly assigned to one of four different survey versions, the four configurations given by changing the order of the two belief elicitation sections and presenting the fertilizers in the BDM auction in two different orders.

At the start of the survey, trained enumerators informed respondents that they would be given 4,000 Tanzanian shillings (TSh) (about $1.74) at the beginning of the survey that was theirs to use however they wanted, 1,000 TSh at the end, and up to 8,000 TSh more depending on their choices during a game during the survey (a risk and ambiguity preference elicitation module). The 4,000 TSh at the beginning of the survey was to ensure all farmers were able to bid during the BDM auction. Note that the median daily income for most smallholder farmers in Tanzania is less than 2,000 TSh (*Tanzania Agriculture Niche Report: Dedicated Farmers*, 2017).

The beginning of the survey recorded information on the farmer's household demographics, then a second module elicited information on their farming activity and use of mineral fertilizer. The survey asked farmers to report their closest geographic market where mineral fertilizer is usually sold. Farmers were asked to provide a different market than Morogoro Town if they initially named Morogoro Town. The reported closest market then was used as the "local market" when eliciting the farmer's beliefs about expected returns to using fertilizer and beliefs about fertilizer quality.

What a farmer is willing to pay for fertilizer is influenced by their subjective beliefs about the expected returns to fertilizer, so after the module on mineral fertilizer use each farmer was asked their subjective beliefs about the yield effects of applying mineral fertilizers of different types. Specifically, farmers were asked how much dry, shelled maize one acre of their farm would produce under five different application scenarios: (1) no fertilizer, (2) 100 kilograms of bad-quality mineral fertilizer, (3) 100 kilograms of best quality mineral fertilizer, (4) 100 kilograms of mineral fertilizer bought at their local market, and (5) 100 kilograms of Morogoro Town bought mineral fertilizer. The government recommends 100 kilograms of mineral fertilizer per acre. Farmers were also asked at what price they could sell this maize to provide an estimate of their expected return to using fertilizer.

To elicit beliefs about fertilizer quality, the survey presented farmers with the following scenario and they answered it twice, once for their local market and once for Morogoro Town: If ten farmers go to that market and each buy a one kilogram bag of fertilizer, how many farmers would receive a bag of good-quality fertilizer? Further, the survey then asked farmers how sure they were about the number of farmers who would get good-quality fertilizer: Completely sure, mostly sure, not sure, or "I have no idea, I am just guessing."

Each farmer also participated in a BDM auction to assess their willingness-to-pay (WTP) for mineral fertilizers with different reported characteristics. In a BDM auction, the participant provides her highest WTP (bid) for the item. Then a random price is drawn. If the drawn price is lower than the bid, the participant buys the item for the randomly drawn price. If the price is higher than the bid, the participant does not buy the item. Each farmer in the study first participated in a BDM auction for a block of laundry soap to help learn the rules of the auction. Then they were presented with a kilogram each of three different fertilizers: urea fertilizer bought in a local market, urea fertilizer purchased in Morogoro Town, and urea fertilizer from a Morogoro Town market that was tested in a lab and assured to be of perfect quality. All three fertilizers were in actuality the same: they had all been acquired in Morogoro Town, lab tested and found to be pure urea. The Morogoro Town market was close to all of the farmers by design and this allowed us to provide partial but true information to farmers in the auction. The farmers gave their bid for each fertilizer, then one fertilizer and its corresponding bid was randomly chosen to be the binding round. After picking the binding fertilizer and bid, the enumerator drew a price to compare to the farmer's bid and complete the auction.

The farmers' beliefs about expected returns to fertilizer, beliefs about fertilizer quality in their local market and Morogoro Town, and WTP for the three different fertilizers are presented in the following chapter. Also presented and discussed is the effect that farmers' beliefs about fertilizer quality have on their WTP for the three different fertilizers.

Chapter 3

Experimental Results

Farmers in the sample believe there are large yield gains to using good-quality mineral fertilizer. Table 3.1 shows the average number of kilograms of dried maize farmers expect that one acre of their land would produce under normal weather conditions after applying 100 kilograms of different qualities of mineral of fertilizer. I did not specify the type of fertilizer, just that it was mineral fertilizer. On average, farmers believe one acre of their farm would produce an additional 910 kilograms of maize when using local fertilizer than without fertilizer – more than a 100% increase over using no fertilizer. Farmers believe that using fertilizer from Morogoro Town would increase this yield by 1,140 kilograms more per acre than without fertilizer, while the best quality fertilizer would increase their yield by 1,180 kilograms more per acre than without fertilizer. They believe that using bad-quality fertilizer would decrease their yields by about 50 kilograms per acre. It should be noted that the expected yield effects of bad-quality fertilizer are just for a single season; farmers in focus groups later revealed that using bad-quality fertilizer could "burn" their soil and reduce its fertility in later seasons.

Taking farmer's reported price at which they could sell maize into account, farmers' expected returns to using fertilizer follow a similar pattern. Table 3.2

Table 3.1: Study participants' expectations about yield effects of using fertilizer. Units are in kilograms of dried, shelled maize per acre of their farm.

	(1)
	Yield Expectation (Mean and Standard Deviation)
No fertilizer	834.15
	(424.22)
100 kgs of locally bought fertilizer	1745.73
	(741.58)
100 kgs of Morogoro bought fertilizer	1977.93
	(731.41)
100 kgs of bad-quality fertilizer	778.36
	(563.03
100 kgs of best-quality fertilizer	2012.21
	(723.40)
Observations	348

shows the expected increase in maize revenue per kilogram of fertilizer for local fertilizer, Morogoro Town fertilizer, and the best quality fertilizer. Expected increases in revenue per kilogram of fertilizer used are higher than the local price of urea fertilizer, about 1,200 TSh per kilogram.

Farmers, however, believed that purchasing bad-quality fertilizer in their local market or in Morogoro Town is a real possibility. Figure 3.1 shows the distribution of these beliefs about fertilizer quality in their local market and in Morogoro Town: 70% of farmers believed that some of their local fertilizer was not good-quality, while 55% of farmers believed that some of the Morogoro fertilizer was not good-quality. On average, farmers believed that 66% of fertilizer in their local market was good-quality, while they believed that 84% of fertilizer in Morogoro town was good-quality.

In addition, farmers are not certain about their beliefs about local fertilizer quality.

Table 3.2: Study participants' expectations about the returns to using fertilizer compared to using no fertilizer, calculated using their yield expectations and reported prices at which they can sell dried, shelled maize. Units are in Tanzanian Shillings per kilogram of fertilizer.

	(1)
	Expected Return, TSh/kg Mean and Standard Deviation
Return per kilogram of local fertilizer	4002.04
	(2827.56)
Return per kilogram of Morogoro fertilizer	5071.78
	(3146.07)
Return per kilogram of best-quality fertilizer	5222.39
	(3049.69)
Observations	344

Figure 3.1: Histogram of study participants' beliefs about the rate of good-quality fertilizer in their local market and in Morogoro Market. Local fertilizer is in green, while Morogoro fertilizer is clear. Mean belief are overlayed for both local and Morogoro.

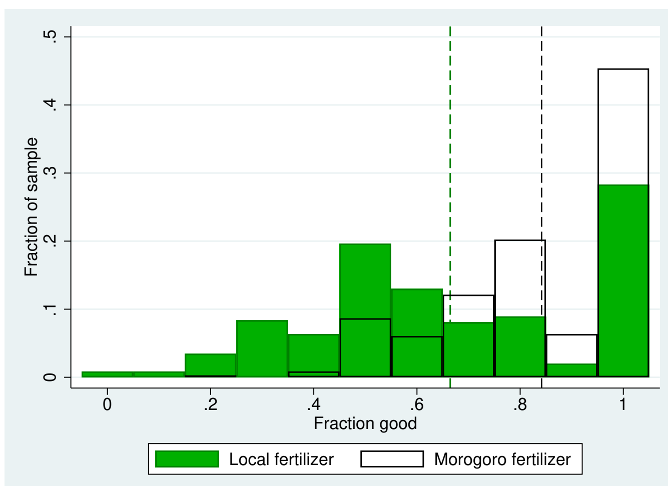
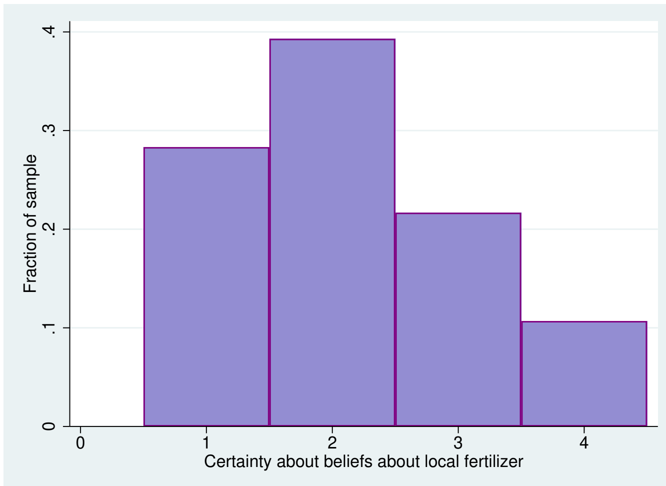


Figure 3.2 shows the distribution of the level of certainty they report in their belief; 28% of farmers report they are completely sure in their beliefs, while 39% report they are mostly sure, 22% say they are not sure of their beliefs and 11% say they

have no idea and are just guessing.

Figure 3.2: Histogram of study participants' certainty in their beliefs about the rate of good-quality fertilizer in their local market.



How do these beliefs relate to what farmers are willing to pay for fertilizer of different (presumed) qualities? Table 3.3 shows the average WTP for local urea fertilizer, urea fertilizer from Morogoro Town, and urea fertilizer from Morogoro Town that was tested and found to be of perfect quality. The average WTP for a kilogram of local urea fertilizer was 1,151 TSh and the average WTP for urea fertilizer from Morogoro Town is not statistically significantly different at 1,199 TSh. At the time of the study, fertilizer prices in local markets were approximately 1,200 TSh. Farmers were willing to pay 46% more for the lab-tested, pure urea fertilizer from Morogoro Town; it had an average WTP of 1,686 TSh.

Beliefs about expected yield returns had no relationship what farmers are willing to pay for fertilizer of different qualities. Using an OLS regression (Wooldridge, 2020), I estimate the relationship between the increase in yield or increase in returns to

Table 3.3: Study participants' willingness-to-pay for locally bought fertilizer, Morogoro Town bought fertilizer, and lab-tested, pure fertilizer.

	(1)
	TSh Mean and Standard Deviation
WTP for local fertilizer	1151.72
	(748.10)
WTP for Morogoro Town fertilizer	1199.71
	(776.02)
WTP for lab-tested, pure fertilizer	1686.96
	(1152.70)
Observations	348

using local, Morogoro Town, and best quality fertilizer and what farmers are willing to pay for locally purchased urea fertilizer, Morogoro Town fertilizer, and lab-tested, pure urea fertilizer purchased in Morogoro Town. Table 3.4 shows the results of this regression; the omitted category is a farmer's WTP for locally purchased fertilizer. The "Tested x Best – Local fertilizer" row measures the effect of the expected increase in yields from using best quality fertilizer over local fertilizer on what a farmer is additionally willing to pay for the lab-tested, pure urea fertilizer in the third column, and the corresponding impact of the increase in returns per kilogram in the fourth. The results indicate that there is little to no correlation between farmers' WTP for local fertilizer and their beliefs about its returns, nor between the premium farmers are willing to pay for Morogoro Town fertilizer or lab-tested, pure urea fertilizer and their beliefs about the additional returns to using those fertilizers over local fertilizer.

Farmers' beliefs about fertilizer quality, however, do have a relationship with what they are willing to pay for fertilizer of different qualities. I estimate the impact of

Table 3.4: Relationship between study participants' WTP for local fertilizer, Morogoro Town fertilizer, and lab-tested, pure fertilizer with their beliefs about the expected yield increases or returns to using local fertilizer, Morogoro Town fertilizer, and lab-tested, pure fertilizer.

	Dependent variable is WTP		
	Village FE	Diff. in Yields	Diff. in Returns
	(1)	(2)	(3)
Morogoro	47.99*	-14.93	44.30
	(0.05)	(0.78)	(0.28)
Tested	535.03***	386.63***	501.67***
	(0.00)	(0.00)	(0.00)
(Local - No fertilizer)		-0.02	-0.01
		(0.76)	(0.69)
Morogoro × (Local - No fertilizer)		0.03	-0.00
		(0.54)	(0.50)
Tested × (Local - No fertilizer)		0.08	-0.00
		(0.25)	(0.98)
(Morogoro - Local fertilizer)		-0.08	-0.00
		(0.53)	(0.98)
Morogoro × (Morogoro - Local fertilizer)		0.10	0.01
		(0.24)	(0.55)
Tested × (Morogoro - Local fertilizer)		0.30*	0.04
		(0.06)	(0.23)
(Best - Local fertilizer)		-0.07	-0.02
		(0.59)	(0.41)
Morogoro × (Best - Local fertilizer)		0.05	0.01
		(0.47)	(0.53)
Tested × (Best - Local fertilizer)		0.02	-0.01
		(0.87)	(0.84)
Constant	1,015.24***	1,069.08***	1,062.97***
	(0.00)	(0.00)	(0.00)
Observations	1,045	1,027	1,024
R^2	0.11	0.015	0.012

Note: Omitted category is WTP for local fertilizer. Village fixed effects are included in all regressions, as are controls for demographic and farming characteristics. Standard errors are clustered at the farmer level. P-values are shown beneath coefficients. *p<0.1; **p<0.05; ***p<0.01.

farmers' beliefs about the fraction of good-quality fertilizer in their local market and Morogoro Town on what they are willing to pay for the three types of fertilizer. Table 3.5 shows these results. On average, farmers are willing to pay 46% more for the tested fertilizer than for local fertilizer. Row 3 shows that farmers are willing to pay 3.6% more for local fertilizer for every 10% increase in their belief about local fertilizer quality, and Row 5 shows that the same increase in beliefs about local fertilizer quality makes farmers willing to pay 4.3% less for tested fertilizer. Farmers with full belief in the quality of local fertilizer have no premium for tested fertilizer.

That farmers' beliefs about the returns to using fertilizer don't correlate with their WTP for fertilizer while their beliefs about fertilizer quality *do* correlate with their WTP for fertilizer could be due to at least a few possible reasons. Farmers beliefs about returns are for using 100 kilograms of fertilizer while they just bid for one kilogram of fertilizer; many farmers told my enumerators that they were going to use the fertilizer from the BDM auction on their vegetables, so the disconnect in size between 100 kilograms and one kilogram and the immediacy of actually using the one kilogram of fertilizer on their vegetables could be driving the non-correlation and correlation.

Farmers' certainty in their beliefs about local fertilizer quality further affect their WTP for local urea fertilizer and the lab-tested, pure urea fertilizer. Table 3.6 shows the results of regressing WTP on how certain a farmer is about their belief about local fertilizer quality. Certainty about beliefs are categorical variables, so there is not one coefficient on "certainty." The interpretation of the results is that farmers monotonically decrease their willingness to pay for local urea fertilizer and

Table 3.5: Correlation between study participants' WTP for local fertilizer, Morogoro Town fertilizer, and lab-tested, pure fertilizer and their beliefs about the rate of good-quality fertilizer in their local market.

	Dependent variable:
	WTP
	(1)
Morogoro	-221.96*
	(0.08)
Tested	406.63*
	(0.07)
Fraction good in local market	366.94**
	(0.03)
Morogoro × Fraction good in local market	-278.06***
	(0.01)
Tested × Fraction good in local market	-427.80**
	(0.04)
Fraction good in Morogoro	-250.05
	(0.35)
Morogoro × Fraction good in Morogoro market	540.05***
	(0.00)
Tested × Fraction good in Morogoro market	484.57
	(0.15)
Constant	999.59***
	(0.00)
Observations	1,036
R^2	0.14

Note: Omitted category is WTP for local fertilizer. Village fixed effects are included in all regressions, as are controls for demographic and farming characteristics. Standard errors are clustered at the farmer level. P-values are shown beneath coefficients. *p<0.1; **p<0.05; ***p<0.01.

monotonically increase their WTP for lab-tested, pure urea fertilizer the less certain they are in their belief about local fertilizer quality. If a farmer is the least certain they are willing to pay 34% less for local urea fertilizer and 12% more for lab-tested, pure urea fertilizer.

Table 3.6: Correlation between study participants' WTP for local fertilizer, Morogoro Town fertilizer, and lab-tested, pure fertilizer and the certainty of their beliefs about the rate of good-quality fertilizer in their local market.

	Dependent variable:
	WTP
	(1)
Morogoro	48.51
	(0.10)
Tested	487.13***
	(0.00)
Mostly sure	-12.37
	(0.90)
Not sure	-142.94
	(0.25)
No idea	-367.15**
	(0.02)
Morogoro × Mostly sure	25.38
	(0.67)
Morogoro × Not sure	-27.18
	(0.67)
Morogoro × No idea	-44.35
	(0.30)
Tested × Mostly sure	22.80
	(0.82)
Tested × Not sure	90.20
	(0.41)
Tested × No idea	194.55
	(0.19)
Constant	1,073.96***
	(0.00)
Observations	1,341
R^2	0.019

Note: Omitted category is WTP for local fertilizer. Village fixed effects are included in all regressions, as are controls for demographic and farming characteristics. Standard errors are clustered at the farmer level. P-values are shown beneath coefficients. *p<0.1; **p<0.05; ***p<0.01.

Chapter 4

Explaining, Modeling, and Simulating Beliefs about Fertilizer Quality

Results presented in the previous section demonstrate that farmers' beliefs about fertilizer quality in their local market and the certainty with which they hold those beliefs have a strong relationship with the premium that farmers are willing to pay for lab tested, pure fertilizer. Farmers have a 46% higher willingness to pay for lab-tested, pure quality urea fertilizer than for local urea fertilizer of unknown quality. In addition, farmers believe 66% of fertilizer in their local market was good-quality and 84% of fertilizer in Morogoro Town was good-quality. For every 10% increase in their belief about the quality of local fertilizer, farmers are willing to pay 3.6% more for local fertilizer and 4.3% less for tested fertilizer, and farmers are willing to pay monotonically less for local fertilizer and monotonically more to lab-tested, pure quality fertilizer the less certain they are in their belief about local fertilizer quality.

The puzzle is that repeated testing has shown that the fertilizer in local marketplaces is actually of high-quality. Michelson et al. (2020) and Maertens, Magomba, and Michelson (2020) tested urea fertilizer from every agro-dealer in Morogoro Region in 2015-16 and a random sub-sample in 2019. Tests of over 800 samples from these testing rounds have found that nearly all had the required nutrients. Furthermore, more than 300 samples collected from farmers by

Michelson et al. (2020) tested as high-quality with the required nutrient levels. Michelson et al. (2020) also tested fertilizer at the port in Dar es Salaam and at the Yara Tanzania warehouses in Dar es Salaam in 2019 and found that all samples had the required nutrients. Two recent reports by the International Fertilizer Development Center also found the prevalence of low-quality fertilizer to be low in Uganda and Kenya, respectively, and a 2019 report by the International Food Policy Research Institute found that fertilizer in Uganda was not missing nutrients (Sanabria, Ariga, Fugice, & Mose, 2018b, 2018a; Ashour, Billings, Gilligan, Jilani, & Karachiwalla, 2019).

The incorrect belief that farmers have is not that poor quality fertilizer can exist, but their belief in the rates at which it exists. It is of course possible that poor quality fertilizer exists in the market and that it is a rare but costly phenomenon for farmers. Extreme rarity could make it unlikely that testing would catch it. Farmers are aware of the possibility of poor quality fertilizer existing in their marketplaces and place a higher probability of it occurring due to lack of experience buying fertilizer in the marketplace. However, if the rates of poor quality fertilizer are what farmers in the study believe – 34% in their local marketplaces and 16% in Morogoro Town – then the testing conducted should have identified some evidence of its presence.

Farmers appear to hold incorrect beliefs about fertilizer quality in their local marketplace, and those incorrect beliefs have strong effects on the premium that farmers are willing to pay for lab tested, pure fertilizer. Yet the fertilizer already available in those local marketplaces is of pure agronomic quality. Persistent, incorrect beliefs depress farmer's willingness to pay for the fertilizer in their local marketplace.

Economic theory of information suggest that beliefs should converge to the truth over time. Why are these incorrect beliefs persisting?

4.1 January 2020 Trip Results

Follow-up work conducted in January 2020 was designed to understand and describe local beliefs about mineral fertilizer using qualitative interviews with extension agents and agro-dealers, farmer focus groups, and discussions with stakeholder organizations, government regulators, and businesses relevant to fertilizer. I ran focus groups in four villages with five smallholder farmers each, two in the Morogoro Rural district and two in the Kilosa district in Morogoro Region, districts where I ran the experiments in July 2019. I interviewed the agricultural extension agent for each village and six agro-dealers in Morogoro Town and the surrounding area.

The focus groups with farmers centered on:

1. Farmers' experience with mineral fertilizer,
2. Farmers' beliefs about the benefits and drawbacks of mineral fertilizer and the sources of those beliefs,
3. Where, how, and when farmers purchased fertilizer,
4. What farmers believed was good-quality fertilizer and how they ascertained fertilizer quality before, during, and after purchase, and

5. What farmers had heard about the quality of fertilizer from different sources including the media and their neighbors.

In general, farmers reported that good-quality fertilizer was beneficial for crop production; it would make crops grow “fast and strong,” give “high and good yields,” and crops with fertilizer would perform better than crops with no fertilizer. Most 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 heard about these benefits from fellow farmers, extension agents, agro-dealers, and the fertilizer companies themselves. However, when it came to what the farmers thought was “good-quality” fertilizer, just one farmer mentioned the chemical content of the fertilizer. The rest commented on the packaging of the fertilizer, the storage conditions, or the physical characteristics of the fertilizer. Farmers also told personal stories about how they knew of farmers who had bought what they referred to as “fake fertilizer.” Farmers seemed to believe that fertilizer quality is binary; either the fertilizer is *safi kabisa* (roughly, “exactly good”) or not. Farmers did not present viewpoints that fertilizer quality could be on a continuum; it was either good-quality or it was bad.

The interviews with extension agents and agro-dealers focused on farmers’ beliefs about fertilizer and buying habits. Extension agents confirmed that farmers thought that good-quality fertilizer was beneficial. Agro-dealers provided insight into the simplified process farmers believed about the relationship between fertilizer and crop yields. Farmers buying fertilizer wanted to be assured that they would get good results. However, agro-dealers explained that farmers often lacked knowledge about why they needed fertilizer. One said the majority of his customers were farmers with no knowledge about which fertilizer to use; farmers would just come in and ask him for “fertilizer for planting or growing or topdressing.” Another related how farmers picked fertilizers based on those used in trial plots ran by fertilizer companies to show off the effects of new fertilizers, expecting to get the same high yields as the crops in the trial plot yet unaware the trial plot was an idealized growing environment with the best quality seeds, pesticides, herbicides, and management.

Conversations with individuals working in non-governmental, business, and governmental organizations related to fertilizer reported that farmers frequently complain about poor quality, fake fertilizer. Farmers’ complaints happen after using fertilizer and seeing bad yield realizations; farmers who use fertilizer and see a bad yield blame it on the fertilizer because they expected good results from using fertilizer. An officer at the Tanzania Fertilizer Regulatory Authority described how tobacco farmers from different regions of Tanzania complained that they had used a fake blended fertilizer after their plants grew yellow and stunted after applying that fertilizer. He traveled to the region and tested the fertilizer based on these reports and test results indicated that the fertilizer in question was pure. Similarly, training officers at Mtandao wa Vikundi vya Wakulima Tanzania (roughly, the National Network of Farmers’ Groups in Tanzania) provided stories about how their member farmers complained about fake fertilizer after getting bad yield results after applying fertilizer. They said how farmers expected to get the high yields “promised to them” by fertilizer companies and agro-dealers after using fertilizer, so when they experienced poor yields blamed the fertilizer. Conversations with the African Fertilizer and Agribusiness Partnership and the Alliance for a Green Revolution for Africa provided insight consistent with the experience of agro-dealers: many smallholder farmers with whom the organizations worked had little experience with fertilizer and limited understanding of fertilizer's specific role in the growing process.

The focus groups, interviews, and meetings provide insight into rural smallholder farmers' beliefs about and use of mineral fertilizer in Tanzania. Farmers do not fully understand the role of fertilizer in crop cultivation and yields and they tend to think fertilizer is of binary quality: good fertilizer leads to good yield results and bad fertilizer leads to bad yield results. These insights suggest that farmers also may think that using fertilizer and then having lower than expected yields implies the fertilizer was bad.

4.2 Literature

I connect three strands of literature to rationalize and model the persistence of incorrect beliefs about fertilizer quality. The first explores the effects of asymmetric information about product quality. The second is on possible reasons for the existence and persistence of incorrect beliefs. The third is on learning, namely agricultural learning in low-income countries and models of learning under ambiguity.

Akerlof (1970), Darby and Karni (1973), and Leland (1979) help to define how to think about fertilizer quality in a low-income country. Akerlof (1970) introduced a structure for determining the economic costs of fraud, and in doing so outlined the type of product in which fraud was possible: the quality of the product is asymmetric, with the seller knowing more about the product quality than the buyer. In a low-regulation context such as Tanzania, fertilizer is one such product.

Darby and Karni (1973) took the idea of fraud further and gave more definition to what it meant for product quality to be amenable to fraud. They defined a class of "credence" qualities, where the assessment of their value required additional costly information. The quality of fertilizer is credence, as "credence qualities arise whenever a good is utilized either in combination with other goods of uncertain properties to produce measurable output or in a production process in which output, at least in a subjective sense, is stochastic, or where both occur." The agricultural production process is inherently stochastic, and the inputs used with fertilizer – soil quality and health, herbicides and pesticides, seeds, and weather – all are goods or environmental conditions with properties uncertain to the farmer. Fertilizer quality is also an experience quality; a farmer can learn about the quality of fertilizer, but only after repeated uses. Given that farmers are promised increased yields by fertilizer companies and agro-dealers if they use fertilizer, it makes sense for a farmer to think that fertilizer quality is an experience quality when it is in fact more of a credence quality; therefore, if a farmer thinks fertilizer quality is an experience quality and sees poor yields after using fertilizer, attributing the poor yields to bad fertilizer is a rational action.

Leland (1979) provided possible reasons for information asymmetries to persist. One reason is that eliminating those asymmetries could be more expensive than the potential welfare gain; in the Tanzanian context the perceived welfare gain could be small because fertilizer is already of good-quality. That is not to say there is no welfare gain to eliminating asymmetries; a welfare gain could come from shifting farmers' beliefs about fertilizer quality and therefore being more willing to use fertilizer. In addition, because the price of fertilizer is set by the government, agro-dealers do not have an incentive to prove the quality of their fertilizer. Another is the difficulty of making sellers liable for poor quality products when it is difficult or impossible to infer product failure; in the context of fertilizer, it might be difficult to ascertain the quality of fertilizer from the quality of crops grown due to the effects of other inputs and inherent stochasticity.

A large number of papers explain the existence and persistence of incorrect beliefs through the existence of a faulty learning mechanism. Chen, Iyer, and Pazgal (2010) provide a theoretical analysis of a situation where a consumer is unable to perfectly recall prices when deciding to purchase due to limited memory. Instead, they categorize a price – as "cheap," "less cheap," and so on to "expensive" – and then when faced with a new price rely on past experience associated with the category of the new price to make their purchasing decision. von Thadden (1992) models a situation in which a seller attempts to find an optimal price against a consumer who learns about price signals by recalling only past prices and associated qualities. Spiegler (2006) models how patients reasoning anecdotally on random, casual stories can lead to the existence of a market of "quacks," false doctors whose treatments have no effect on sick patient outcomes, and Piccione and Rubinstein (2003) model how heterogeneous abilities among agents to recognize patterns in signals of information can lead to some agents being unable to learn fully from the signal. More recently, Koçak (2018) presents how sequential updating – a situation in which an agent must choose the order in which to update a prior based on multiple sources of information – leads to different posterior beliefs. In a similar vein, Schwartzstein (2014) shows how selective attention – where an agent must choose *a priori* which signals to attend to – can lead to the agent having systematically biased forecasts and incorrect beliefs.

Four papers that speak most closely to this research, in that they address the difficulty of learning about product quality or agricultural practices in a low-income country, are Björkman-Nyqvist et al. (2020), Adhvaryu (2014), Hanna et al. (2014), and Bold et al. (2017). The first two papers examine how consumers form beliefs about antimalarial medicine in Sub-Saharan Africa, with the former in Uganda and latter in Tanzania. A key difference between these papers and mine is that in the case of antimalarial drugs, there actually is a problem with low-quality, fake medicine in the markets. However, the papers provide insight into my problem. An earlier version of the first finds that biomedical misconceptions about malaria hamper the ability to learn about the quality of antimalarial medicine (Björkman-Nyqvist, Svensson, & Yanagizawa-Drott, 2013). Misconceptions about malaria cause the consumer to attend to the incorrect data provided by treatment. This paper supports my idea that farmers' misconceptions about fertilizer's relationship to yields hinder their learning about its quality. The second finds that misdiagnosis of malaria slows the rate of social learning about the quality of medicine due to adding noise to information available from therapeutic results. If a consumer is incorrectly diagnosed with malaria, then attempting to infer information from their results with a specific antimalarial medicine will be fruitless and overall detrimental to learning about the effectiveness of antimalarials. Increased access to diagnostic technology would help the learning process, argues Adhvaryu. In my situation, a farmer using the wrong fertilizer given the soil in their field or what their crop needs or using it incorrectly is akin to misdiagnosis. Hanna et al. (2014) show how selective attention can cause farmers to continually have sub-optimal practices; seaweed farmers in their paper don't consider pod size to when considering the dimensions along which to learn and subsequently fail to learn how pod size impacts their seaweed yield. Their paper supports my model, in that farmers in my model just select crop yields as the only dimension to learn about the chemical quality of the fertilizer they applied to their field. Bold et al. (2017) show how the noise in yields make it harder for Ugandan farmers to learn about fertilizer quality; however, they argue that is the reason why substandard-quality fertilizer can continue to exist in the market in Uganda. While my paper also considers farmers learning about fertilizer quality, my argument is different: ambiguity and farmers' learning with misattribution causes them to persistently, incorrectly believe the existence of poor quality fertilizer in their markets.

Farmers attempting to learn about fertilizer quality face a complicated, vaguely specified, and poorly understood environment. Agricultural noise obscures the signals they receive about fertilizer quality. Further, multiple different sources tell them different things about fertilizer quality: Fertilizer companies and agro-dealers promote fertilizer's high quality while fellow farmers, newspaper reports, and some farmer advocacy groups warn of poor quality fertilizer (Kasumuni, 2016). Taking ambiguity into account, farmers in my model have multiple priors about fertilizer quality instead of a single prior. Gilboa and Schmeidler (1989) introduced the concept of multiple priors, Epstein and Schneider (2003) axiomatized a multiple prior learning process, and Epstein and Schneider (2007) introduced the decision-making process I use: Given a realization of the data, the farmer performs a likelihood ratio test for each of their beliefs against their most likely belief and only keeps and updates those which pass the test. Multiple priors are apt for farmers learning about fertilizer quality; multiple priors have been applied in finance (Garlappi, Uppal, & Wang, 2007; Epstein & Schneider, 2008, 2010; Ilut & Schneider, 2014), and are particularly well suited to model situations where agents receive ambiguous signals in poorly defined environments (Bland & Rosokha, 2019; Cubitt, van de Kuilen, & Mukerji, 2020).

4.3 Learning Model

In the model, the farmer thinks that the rate of good-quality fertilizer follows a Bernoulli(p) distribution - I learned that farmers think that fertilizer is either good-quality or bad-quality. In period zero, the farmer has a set of active priors $\mathcal{P}^0 = \{\pi^0(\theta_1),\, \pi^0(\theta_2), \ldots,\, \pi^0(\theta_k)\}$ about the value of p and an empty set $\mathcal{D}^0$ of discarded, or inactive, priors. The farmer learns about p by observing the yield realizations $\mathbb{Y}^1 = \{y^1_1,\, y^1_2, \ldots,\, y^1_n)$ of all her n neighbors who use fertilizer. While there are more than n farmers in the village, the farmers just learns about fertilizer quality from the yields of the n farmers who use fertilizer. Every yield realization in each period follows a linear growing process with mean μ and a "noise" following a $N(0,\, \sigma^2)$ distribution. If a yield falls below a certain threshold s_l, then the farmer attributes "bad fertilizer," or a failure, to that plot; conversely, if the yield is above $s_h > s_l$, the farmer attributes "good fertilizer," or a success, to that plot. A yield in between the two thresholds doesn't provide the farmer with information so is ignored when updating. The farmer's inferred fertilizer quality for an informative yield y_i^1 is denoted as x_i^1. Given that the farmer thinks that the rate of good-quality fertilizer follows a Bernoulli(p) distribution, the informative yields $\mathbb{X}^1 = \{x_1^1,\, x_2^1, \dots\, ,\, x_m^1\}$ follows a Binomial(m, p) distribution. Given the data $\mathbb{X}^1$, a prior $\pi^0(\theta)$ is updated to $\pi^1(\theta) = \pi^0(\theta \mid \mathbb{X}^1)$ according to Bayes' Rule:

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

Where

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

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

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

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

$$\mathcal{P}^1 = \left\{ \pi^1(\theta) \mid \pi^0(\theta) \in \mathcal{P}^0,\ \frac{L(\mathbb{X}^1 \mid \pi^0(\theta))}{L(\mathbb{X}^1 \mid \pi^0(\theta^*))} \geq \gamma \right\} \tag{4.1}$$

Discarded priors go into a set of discarded priors $\mathcal{D}^1$. The likelihood-ratio test is also performed on discarded priors; if a discarded prior passes the likelihood-ratio test it gets updated and goes back into the set of active priors. The evolution of the farmer's beliefs over time are given by the priors in the set of active priors.

A flexible prior is needed to model the farmer's beliefs. The farmer thinks that fertilizer quality is binary, but she knows that she does not know the share of good-quality fertilizer in the market. The Beta-Binomial(m, p, α, β) distribution allows for modeling this situation. The random variable of the number of successful informative trials, call it X, follows a Binomial(m, p) distribution, while the parameter of the Binomial distribution p follows a Beta(α, β) distribution. The farmer attempts to learn about p.

Dropping indices for brevity,

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

Which means

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

And

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

Given a number of successes k out of m informative trials, we need to find out how to update a given prior. The posterior is proportional to the likelihood of seeing the data multiplied by the prior distribution. Thus, again dropping indices to allow for cleaner derivations, the posterior $\pi(p \mid m, k, \alpha, \beta)$ is given by:

$$\begin{aligned} \pi(p \mid m, k, \alpha, \beta) &\propto L(k \mid m, p)\pi(p \mid \alpha, \beta) \\ &= \binom{m}{k} p^k (1-p)^{m-k} \frac{p^{\alpha-1}(1-p)^{\beta-1}}{\mathrm{B}(\alpha, \beta)} \\ &\propto p^{\alpha+k-1}(1-\alpha)^{\beta+m-k-1} \end{aligned} \tag{4.2}$$

We see that the updated α parameter is just the prior value plus the number of successes, and the updated β parameter is just the prior value plus the number of failures.

To perform the likelihood ratio test, we need to know the likelihood of seeing k for given m, α, and β values, $p(X = k \mid m, \alpha, \beta)$. This is given by:

$$\begin{aligned}
p(X = k \mid m, \alpha, \beta) &= \int_0^1 p(X = k \mid m, p)\pi(p \mid \alpha, \beta) dp \\
&= \int_0^1 \binom{m}{k} p^k (1-p)^{m-k} \frac{p^{\alpha-1}(1-p)^{\beta-1}}{\mathrm{B}(\alpha, \beta)} dp \\
&= \binom{m}{k} \frac{1}{\mathrm{B}(\alpha, \beta)} \int_0^1 p^k (1-p)^{m-k} p^{\alpha-1} (1-p)^{\beta-1} dp \\
&= \binom{m}{k} \frac{1}{\mathrm{B}(\alpha, \beta)} \int_0^1 p^{k+\alpha-1} (1-p)^{m-k+\beta-1} dp \\
&= \binom{m}{k} \frac{\mathrm{B}(\alpha + k, \beta + m - k)}{\mathrm{B}(\alpha, \beta)}
\end{aligned} \tag{4.3}$$

4.4 Suggestive Evidence for the Model: Beliefs Correlate with Weather Variability

The learning model suggests that historic weather variability might influence a farmer's beliefs about input quality. Historic weather variability could make it harder for a farmer to learn about input quality and therefore cause them to have an increased variance and range of the distribution of beliefs about the prevalence of good-quality inputs, and to the extent that historic variability correlates with weather shocks, could cause the farmer to have worse beliefs about input quality.

To test this possibility, I use baseline data from the International Food Policy Research Institute (IFPRI) 2014 Uganda Agricultural Inputs Study and daily precipitation data from the Climate Hazards Group InfraRed Precipitation with

Station (CHIRPS) dataset (*Baseline Evaluation of the Impact of E-verification on Counterfeit Agricultural Inputs and Technology Adoption in Uganda: Household Survey*, 2015; Funk et al., 2015). The baseline data and precipitation data, while being from Uganda, can provide suggestive support for my model because of Uganda's similar agricultural environment.

The IFPRI study asked farmers what they believed was the number of bags of bad-quality fertilizer out of ten bags purchased in their local market and further asked what the farmer thought this distribution was. To make the measures consistent with my study in Tanzania, I transform the farmers' distributions to the prevalence of bags of good-quality fertilizer, not bad-quality. This gives us three outcome variables: Mean of the belief distribution, variance of the belief distribution, and range of the belief distribution. I include the range of the belief distribution in addition to the variance because farmers might not use the whole distribution to treat input purchasing and usage as a compound lottery but rather make decisions according to what they believe are the worst and best possible cases they expect. As such, the range of the distribution is a better measure of ambiguity than the variance of the distribution. I also include whether or not the farmer reported experiencing a loss due to drought or flood in the past two years, whether the farmer correctly answered two questions about fertilizer usage, and controls for the farmer's age, education, sex, and literacy.

CHIRPS data have a 0.05-degree spatial resolution, meaning I have daily precipitation for 5.5km2 cells for the IFPRI farmer locations. Precipitation data was gathered for the 30 years prior to the survey dates, July, August, and

September 2014, and transformed into monthly and agricultural season measures of precipitation and precipitation shocks. The study region has two agricultural seasons for maize, one from February to May and another from September to November. As such, the agricultural season from February to May in 2014 is denoted the ”previous first agricultural season” and the agricultural season from September to November 2013 is ”previous second agricultural season.”

The broadest measure of the historic rainfall variability is the variance of the daily rainfall during both agricultural seasons in the previous 30 years. As the first season is the “long season” it might have more of an effect on the farmer’s beliefs, so I further split up historic variability into the variance of the daily rainfall in each agricultural season during the previous 30 years. In addition, precipitation variance during planting affects yields differently than variance during growing, so I further split up historic variability into the variance of daily rainfall in each month in each agricultural season during the previous 30 years.

I regress the mean, variance, and range of the farmers’ believed distributions of good-quality bags of fertilizer on variance in daily rain during the growing seasons in the previous 30 years using OLS. An increase in the variance of daily rain during the growing seasons over the previous 30 years is significantly correlated with a decreased mean, variance, and range of the farmers’ believed distribution of good-quality bags of fertilizer. Results are in shown in Table 4.1.

Breaking up by season, most of these effects are driven by variance in the first agricultural season (Table 4.2). This could be due to the fact that more farmers use fertilizer during the first agricultural season than the second agricultural season.

Table 4.1: Correlation between IFPRI study participants' distribution of their believed rates of good-quality fertilizer in their local market and their local variance of daily precipitation during the two growing seasons for the 30 years prior to interview.

	Dependent variable:		
	Mean of Distr.	Var. of Distr.	Range of Distr.
	(1)	(2)	(3)
Constant	0.554***	0.012*	0.278***
	(0.000)	(0.062)	(0.003)
Hist. Var.	−0.002**	0.0001*	0.002**
	(0.017)	(0.058)	(0.016)
Observations	1,341	1,341	1,385
R^2	0.019	0.007	0.016

Note: Standard errors are clustered at the market level. P-values are in parentheses below the coefficients. *p<0.1; **p<0.05; ***p<0.01

Table 4.2 shows that an increase in the variance in the second agricultural season is significantly correlated with an increase in the mean of the believed distribution, but a regression of the mean on just variance in the second agricultural season shows that this is not true (Table 4.4). This could be due to the effects of collinearity between the seasons; an area with higher variance during the first agricultural season is going to have higher variance during the second agricultural season.

It is important to note that the correlation between historical rainfall variation and farmers' beliefs about fertilizer quality is not a causal relationship; what I find is a correlation, suggestive evidence that implications of my learning model might hold. For example, a locale with higher precipitation variance over time might have had less surplus in yields and experienced less market buildup, which could affect farmers' beliefs about input quality. However, the fact that a correlation exists suggests a possible relationship between weather variability and farmers' beliefs about the

Table 4.2: Correlation between IFPRI study participants' distribution of their believed rates of good-quality fertilizer in their local market and their local variance of daily precipitation during the first growing season and during the second growing season for the 30 years prior to interview.

	Dependent variable:		
	Mean of Distr.	Var. of Distr.	Mean of Distr.
	(1)	(2)	(3)
Constant	0.514***	0.014**	0.304***
	(0.000)	(0.029)	(0.001)
Hist. Var. in Season One	−0.004***	0.0002***	0.003***
	(0.0003)	(0.005)	(0.005)
Hist. Var. in Season Two	0.002*	−0.0001	−0.001
	(0.065)	(0.138)	(0.318)
Observations	1,341	1,341	1,385
R^2	0.025	0.010	0.019

Note: Standard errors are clustered at the market level. P-values are in parentheses below the coefficients. *p<0.1; **p<0.05; ***p<0.01

Table 4.3: Correlation between IFPRI study participants' distribution of their believed rates of good-quality fertilizer in their local market and their local variance of daily precipitation during the first growing season for the 30 years prior to interview.

	Dependent variable:		
	Mean of Distr.	Var. of Distr.	Range of Distr.
	(1)	(2)	(3)
Constant	0.560***	0.011*	0.282***
	(0.000)	(0.061)	(0.002)
Hist. Var. in Season One	−0.003***	0.0001**	0.002***
	(0.002)	(0.014)	(0.005)
Observations	1,341	1,341	1,385
R^2	0.022	0.009	0.018

Note: Standard errors are clustered at the market level. P-values are in parentheses below the coefficients. *p<0.1; **p<0.05; ***p<0.01

Table 4.4: Correlation between IFPRI study participants' distribution of their believed rates of good-quality fertilizer in their local market and their local variance of daily precipitation during the first growing season for the 30 years prior to interview.

	Dependent variable:		
	Mean of Distr.	Var. of Distr.	Range of Distr.
	(1)	(2)	(3)
Constant	0.484***	0.015**	0.325***
	(0.000)	(0.016)	(0.0004)
Hist. Var. in Season Two	−0.001	0.00002	0.001
	(0.630)	(0.723)	(0.330)
Observations	1,341	1,341	1,385
R^2	0.015	0.004	0.013

Note: Standard errors are clustered at the market level. P-values are in parentheses below the coefficients. *p<0.1; **p<0.05; ***p<0.01

quality of agricultural inputs.

4.5 Simulating the Learning Process

To compare the effects of different policies intended to increase the use of mineral fertilizer, I simulated policies using the learning model in Python.

The required inputs that I can alter are the number of farmers, the number of priors along with their means and variances, the mean of the yield realizations and the standard deviation of its noise, the threshold below which a farmer considers a yield a failure, the threshold above which a farmer considers a yield successful, and the learning parameter γ. I chose to specify the mean and variance of the priors as opposed to their hyperparameters because the mean and variance are more easily interpreted than α and β. There are two alternate inputs, the number of time periods and a target belief. A simulation with the required inputs and the number of time period studies how beliefs evolve of the the time periods. A simulation with the required inputs and a target belief studies how many time periods it takes for the farmer's beliefs to reach the target belief. The input variables and their descriptions are in Table 4.5.

Table 4.5: Variables that can go into a simulation along with their description.

Input Variable	**Description**
	Required
N	Number of farmers
Priors	Array of priors; dimensions are (number of priors) $\times$ 2 $\times$ 1; the first dimension denotes a specific prior, the second dimension has the expectation of a prior in the first coordinate and the variance in the second, and the third dimension records the period
M	Mean of the yield realizations
S	Standard deviation of the noise in the yield realizations
Low threshold	Threshold below which a yield is denoted a failure by the farmer
High threshold	Threshold above which a yield is denoted a success by the farmer
γ	Learning parameter for the likelihood-ratio test
	Alternate
T	Number of periods
Target belief	Target belief for which the mean of the expectation of the farmer's active beliefs much be at or above to stop the simulation and return the number of periods it took to reach the target belief

If farmers' beliefs about fertilizer quality are determinants in their decision to adopt fertilizer, it is important to understand the effects of policies intending to increase fertilizer use on farmer's beliefs. It is also of interest to understand the effects of multiple priors and misattribution inherent to my model. To do this I simulate different situations using the learning model.

To calibrate the model, I need an estimate of the number of farmers using inorganic fertilizer in a village and the mean of the growing process and standard deviation of the noise in the growing process. I divided the population of each village in the Morogoro Rural and Kilosa Districts of Morogoro Region by the average household size in Morogoro Region (4.7) to get an idea of the number of households in each village (*Tanzania Population and Housing Census*, 2012). I multiplied that number by the share of agricultural households in Morogoro Region (0.98) to get the number of agricultural households in each village, then multiplied that number again by the share of households using inorganic fertilizer in Morogoro Region (0.13) to get the number of inorganic fertilizer using households in each village (*Agriculture Sample Census Survey*, 2008). I took the median of that number for all villages (52) and set it as the baseline number of farmers in the model.

I set the mean of the yield realizations and the standard deviation of the noise in the yield realizations using experimental data from (Bold et al., 2017); the mean is 1.82 dried metric tons of maize per hectare and the standard deviation 0.5278. I also set the number of periods to 25 (running the simulations with different number of periods do not substantively change the results).

When I run a simulation, the two statistics of interest at the end of the time periods are: What does the farmer believe, and what are the range of the farmer's beliefs? Given that there can be active multiple priors at a given time, I define what a farmer believes as the average of the expectation of the active priors and the range of the farmer's beliefs as the range between the two furthest expectations of the active priors. To put the belief into context, I present it as the distance to the true parameter. The true parameter governing the proportion of good fertilizer is one, so this means the statistics are presented on a scale of 0-1, where the smaller the distance the closer to truth the belief is.

Each time I run a simulation, however, the two statistics of interest vary due to the stochasticity in the model. When comparing two policies, then, it is not enough to run a simulation once for each policy. I run the simulation 1000 times for each situation or policy and compare the distributions of the two statistics of interest. I ran a simulation of a baseline situation to initialize some effects against which to compare policies. In the baseline situation the farmer misattributes poor yields to bad-quality fertilizer and has nine priors about fertilizer quality; the expectations run from 0.1 to 0.9 and the variance of each is 0.01. To examine the effects of multiple priors I run a simulation where the farmer has one uniform prior but still misattributes. To examine the effects of misattribution I run a simulation where the farmer has the same priors but does not misattribute. The results of each simulation are presented in Table 4.6.

The policies I studied within my framework are a fertilizer subsidy program, a plot-specific fertilizer recommendation program, an information campaign telling farmers that fertilizer quality is good, and an educational program on how fertilizer works in the growing process. A fertilizer subsidy increases the number of farmers who can use fertilizer, increasing the number of farmers by (for example) 50% from 52 to 78. An

Table 4.6: The effects of different policies on a farmer's beliefs, simulated using the learning model.

Simulation situation	Effect on simulation	Mean of distances from truth	Variance of distances from truth	Mean of ranges of active expectations	Variance of ranges of active expectations
Baseline	No effect	0.2429	0.0009444	0.064004	0.0025606
Uniform prior	One uniform $[0, 1]$ prior instead of multiple priors	0.1672	0.0001787	None	None
No misattribution; "education program"	Farmer does not attribute poor yields to bad fertilizer, instead just attributes good yields to good fertilizer	0.01295	1.326e-7	0.01968	3.049e-7
Fertilizer subsidy	Increase number of farmers using fertilizer by 50% to 78 from 52	0.2378	0.0006647	0.04747	0.001565
Information campaign that fertilizer is good quality	Get rid of lowest four priors; remaining priors have expectations of 0.5, 0.6, 0.6, 0.8, and 0.9	0.2373	0.0005179	0.0504	0.001234
Plot-specific fertilizer recommendations	The yield below which a yield is attributed to bad fertilizer is lowered (percentile goes to 0.1 instead of 0.15)	0.1793	0.0008666	0.05497	0.002598

information campaign could convince farmers that some of their worst initial beliefs about fertilizer quality are not correct; this is operationalized in the simulation by removing the four worst priors. A plot-specific fertilizer recommendation program could give farmers more confidence in the effects of the fertilizers they chose to use; this is operationalized in a simulation by lowering the threshold below which a farmer misattributes yields to bad fertilizer. An educational program on how fertilizer works in the growing process could help farmers understand that fertilizer is not a silver bullet and that poor yields could be due to weather, pests, or disease; this is operationalized in a simulation by removing misattribution altogether. Table 4.6 describes how these policies affect parameters in the simulations.

Looking at the simulation results, the baseline situation has a mean distance from the truth (the rate of good-quality fertilizer is 1) of 0.2429 and a mean range of expectations of 0.06404; put in context, the farmer on average expects that the rate of good-quality fertilizer could be between 0.725 and 0.789. Multiple priors exacerbate the incorrect belief and range of beliefs, as shown by the uniform prior situation. The expectation of a uniform prior is the same as the average of the expectations of the multiple priors, yet having one uniform prior reduces the mean distance from the truth to 0.1672 and eliminates a range of possible beliefs. Misattribution significantly worsens beliefs; without misattribution the mean distance from the truth is just 0. 01295 with a mean range of expectations of 0.01968. Even with multiple priors, the farmer expects the rate of good-quality fertilizer to be between 0.977 and 0.997.

The effects of policies are varied. A subsidy does not substantively change what a farmer believes about the rate of good-quality fertilizer. The mean distance from the truth reduces slightly to 0.2378 from 0.2429, and the mean range of expectations reduces significantly to 0.04747 from 0.064004. A subsidy helps farmers learn about the quality of fertilizer by increasing the number of farmers using fertilizer, but without addressing the issue of misattribution farmers learn incorrectly and incorrect beliefs persist.

An information campaign that fertilizer quality is good does not help substantively change what a farmer believes about the quality of fertilizer, either. The distance from the truth remains almost unchanged and the range of expectations also remains almost unchanged. Again, this illustrates that policies ignoring misattribution will fail to shift incorrect beliefs.

Plot-specific fertilizer recommendations do address misattribution, albeit indirectly, and their effects on beliefs are evident. The mean distance from the truth reduces significantly to 0.1793 from 0.2429, and the range of expectations remains about the same. The mechanism of misattribution still exists, but the increased confidence in the effects of fertilizer means it takes a worse yield than baseline for the farmer to think it was due to bad fertilizer.

The most effective policy is the education program about how fertilizer works in the growing process, ostensibly correctly treating misattribution. Beliefs in this scenario almost converge to the truth and have the smallest ranges of possibilities. This sort of policy should help a farmer correctly infer information about the quality of fertilizer from yield realization; when a farmer is able to learn correctly their beliefs converge to the truth and their confidence in their belief is reduced significantly.

Diving deeper, to compare the beliefs of a farmer with and without a subsidy program (n = 52, n = 78), I can plot the empirical probability distribution functions (PDFs) and cumulative distribution functions (CDFs) of the distance between the truth and the mean of the expectation of the active beliefs for each scenario. The empirical PDFs (Figure 4.1) show that the distance from the truth in each scenario is about the same, but the subsidy more tightly bunches beliefs around the mean. The empirical CDFs (Figure 4.2) indicate that the distribution of beliefs under the subsidy just barely lies more to the left than the distribution of beliefs without the subsidy, indicating that slightly more beliefs lie closer to the truth with the subsidy.

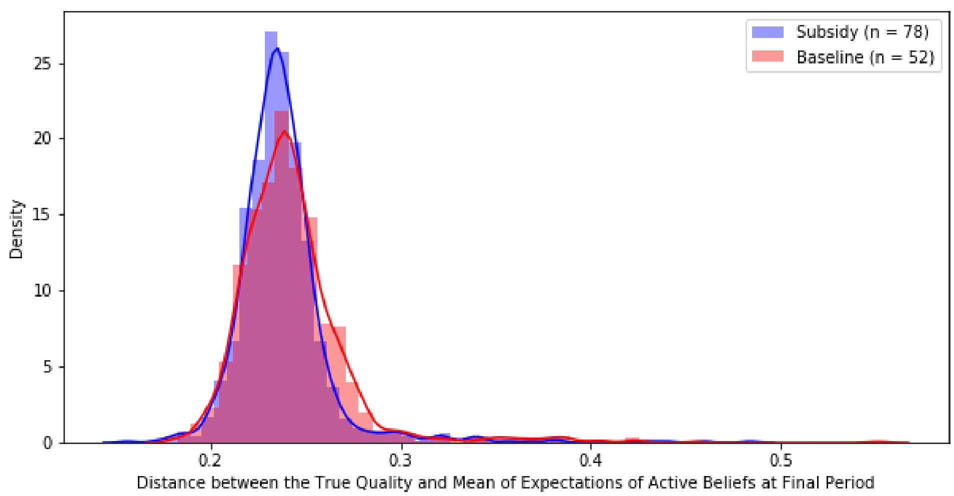


Figure 4.1: Empirical probability distribution function comparing the distance between true quality and the point to which beliefs evolve to for the baseline simulations and the subsidy simulations, for 1,000 simulations each.

To compare the range of beliefs of the farmer for each scenario, I also plot the empirical PDFs and CDFs of the range between the expectation of the worst active belief and best active belief. There are values of zero in the distances between the

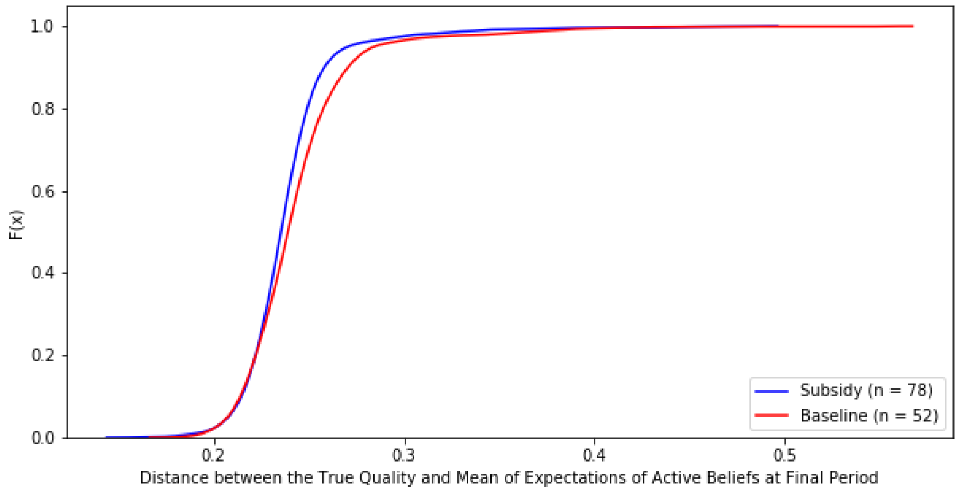


Figure 4.2: Empirical cumulative distribution function comparing the distance between true quality and the point to which beliefs evolve to for the baseline simulations and the subsidy simulations, for 1,000 simulations each.

expectations of active priors in some simulation runs due to there being just one active prior; that is why there are negative values for the empirically determined range. The plot of the empirical PDFs (Figure 4.3) show that the distribution of the range of beliefs is further to the left under the subsidy scenario than without the subsidy. The plot of the empirical CDFs (Figure 4.4) confirms this; there are smaller ranges in beliefs when there is a subsidy than when there is not a subsidy. This is due to there being more farmers from which to learn when there is a subsidy.

Additionally, I altered the simulation to have a target belief instead of the number of periods as an input, and as the output have the number of periods it takes for the average of the expectations of farmer's active beliefs to reach the target belief. For example, for a farmer who has priors, each with variance 0.01 and with expectations

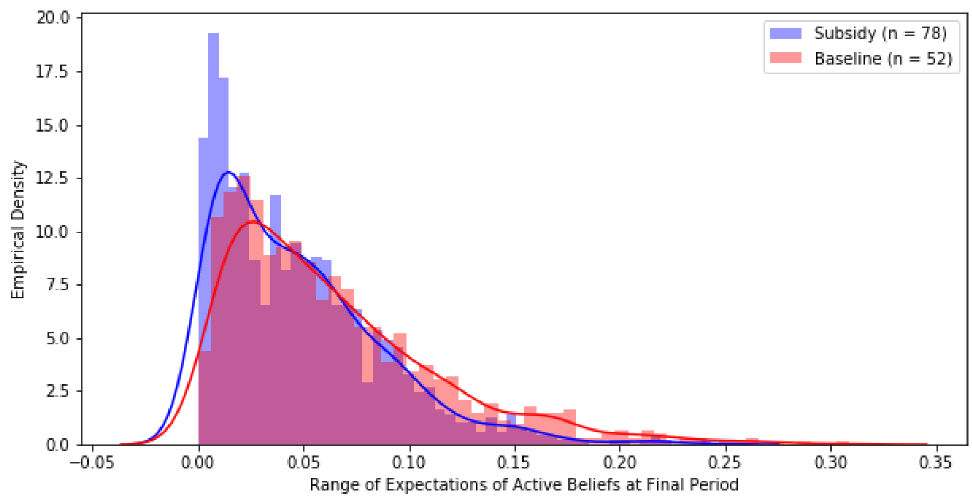


Figure 4.3: Empirical probability distribution function comparing the range between the belief closest to the truth about the rate of good quality fertilizer and the belief furthest from the truth for the baseline simulations and the subsidy simulations, for 1,000 simulations each.

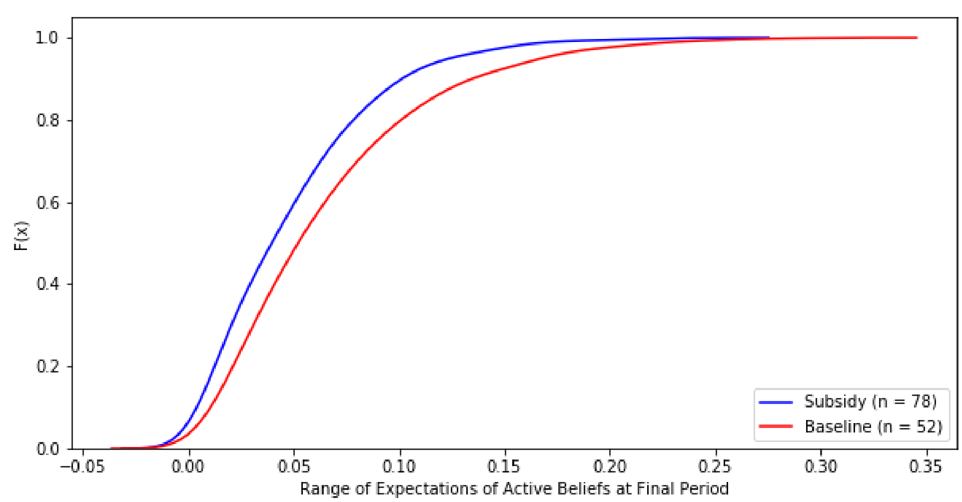


Figure 4.4: Empirical cumulative distribution function comparing the range between the belief closest to the truth about the rate of good quality fertilizer and the belief furthest from the truth for the baseline simulations and the subsidy simulations, for 1,000 simulations each.

ranging from 0.1 to 0.9, and 10 neighbors, I can find the number of periods it takes for the average of the expectations of the farmer's active beliefs to be higher than 0.7, given that it starts at 0.5.

To see if there are nonlinearities in the number of periods it takes to reach different target beliefs or different marginal values in adding neighbors from which to learn, I vary target beliefs from 0.7 to 0.8 and run 100 simulations of the number of periods it takes to reach that target belief for 1 to 50 farmers. For each simulation, the farmer has the same priors as described in the previous paragraph.

The results of the simulations show that there are nonlinearities in the number of periods it takes to reach different target beliefs. Figure 4.5 shows that the average number of periods to reach a target belief increases exponentially as the target belief increases from 0.7 to 0.8. The marginal value of additional neighbors from which to learn diminishes greatly past certain points for each target belief, and that certain point decreases as the target belief increases. It takes more periods to converge to a target belief of 0.75 when there are 5 neighbors compared to when there are 40 neighbors, but takes roughly the same number of periods to converge to a target belief of 0.8 when there are 5 neighbors compared to when there are 40 neighbors. These both lend support to the idea that learning is constrained by the learning mechanism itself past a point, and that past that point learning is not helped by the addition of more farmers from which to learn.

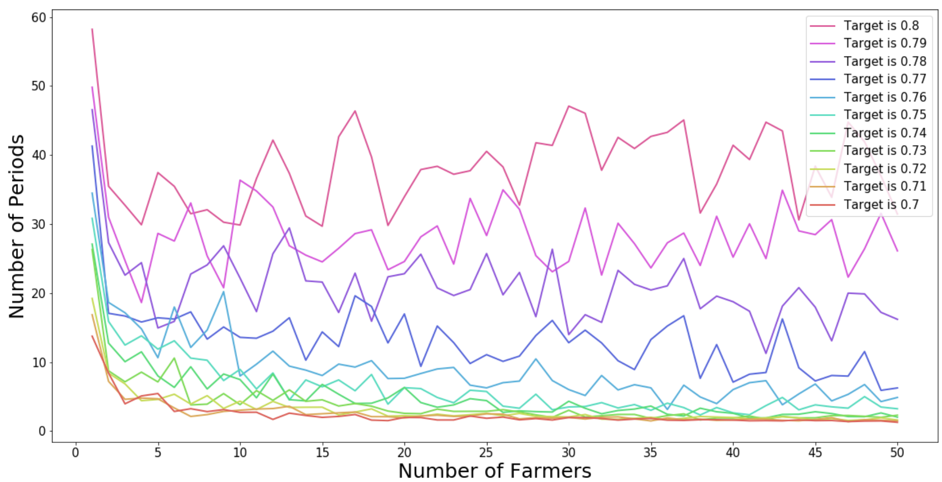


Figure 4.5: For numbers of farmers using fertilizer ranging from 0 to 50, plot of the average number of periods it takes for a farmer's beliefs to reach target beliefs ranging from 0.7 to 0.8 over 100 simulations.

Chapter 5

Discussion

I find that rural farmers in Tanzania had incorrect beliefs about the quality of fertilizer in their local markets and that these beliefs have large effects on their willingness-to-pay (WTP) for local fertilizer and lab-tested, pure urea fertilizer.

Farmers may be trying to avoid bad-quality fertilizer. The training officers at Mtandao wa Vikundi vya Wakulima Tanzania reported that farmers believe that bad-quality fertilizer could "burn" their soil and reduce its fertility in future seasons; some farmers in my focus group reported the same concern. If farmers believe that the possible agronomic effects of bad-quality fertilizer are harmful, it makes sense they would have a large WTP for fertilizer of assured-quality. It also makes sense that increased uncertainty in their beliefs about local fertilizer quality would lead to a higher WTP for assured-quality fertilizer; the more uncertain a farmer is about the quality of local fertilizer, the higher they think the possibility of ending up with poor quality fertilizer locally.

Farmers' incorrect beliefs and lack of confidence about those beliefs may be attributable to ambiguity in the learning environment and a misattribution in the learning process. The learning environment is noisy; stochasticity in the growing process obscures the signal farmers can receive about fertilizer quality. Noise also comes in the form of multiple conflicting sources of information about quality itself. Newspapers report on possibilities of fake fertilizer, fertilizer companies and agro-dealers insist their fertilizer is the highest quality, and other farmers provide anecdotal evidence about what they believe about fertilizer quality. All these sources of information manifest themselves in the farmer having multiple priors about fertilizer quality, reducing their confidence in any one belief about fertilizer quality.

Moreover, misattribution contributes to the persistence of incorrect beliefs: farmers attribute a poor yield to bad-quality fertilizer as opposed to problems related to fertilizer type, application, soil quality, or weather shocks. This misattribution can stem from simplifying the relationship between fertilizer quality and yields: all else equal, better quality fertilizer means higher yields; however, having poor quality yields does not mean that the fertilizer was necessarily poor quality. Poor understanding of the proper fertilizer to use for specific field and soil conditions and crop, blanket fertilizer recommendations by the government, and incorrect application (amounts, placement, or timing) of fertilizer further push the actual relationship between fertilizer quality and yields away from the farmers' idealized relationship. Misattribution could also be caused by something else; for example, applying fertilizer could be salient to a farmer, and so easier to blame if the farmer experiences bad yields.

My experiment with smallholder farmers showed that they are willing to pay a 46% premium for lab-tested, pure fertilizer. However, the learning model and simulation suggest that a certification or testing policy might be counter effective without the tools in place to address misattribution. Certification or testing, in the framework of the model, might actually serve to increase farmers' expectations about the effects of fertilizer. These increased expectations could increase the prevalence of misattribution if farmers continue to simplify the relationship between fertilizer and yields while the stochasticity of yields stays the same.

If beliefs that fertilizer is poor quality contribute to farmers' failing to adopt fertilizer, then the puzzle of under-adoption of mineral fertilizer in Sub-Saharan Africa may be less of a mystery. In fact, low use may be rational from the farmer's point of view. Misattribution is a reasonable reaction from a farmer when encountering a poor yield after using fertilizer. For one, farmers are unaware of test results that show fertilizer in their region is all good-quality. Farmers are also aware that fertilizer counterfeiting or adulteration is a possibility; there is little testing by the Tanzania Fertilizer Regulatory Authority and the only assurance farmers have of the chemical contents of fertilizer they are purchasing is the fertilizer bag label. Further, given that fertilizer quality is both a credence quality and experience quality and information on quality is asymmetric in this environment, farmers know that agro-dealers are aware of the viability of counterfeiting or adulterating fertilizer. Finally, farmers are told by fertilizer manufacturers, extension agents, research organizations, and agro-dealers about the big yield benefits of fertilizer. These big yield benefits are under perfect conditions with the right applications of the right fertilizers for the soil at the right times and paired with the best seeds, but farmers do not know that. It then is natural for a farmer to think: "I was told by a multitude of people that if I used fertilizer my yields would increase considerably. I used fertilizer and I got bad yields this year, going against what I was told. Therefore, the fertilizer must have been fake."

It is important to acknowledge the ambiguity farmers face when trying to learn about input quality and the fact that farmers might learn heuristically, allowing incorrect beliefs to persist over time. As shown in the simulations, policies that fail to address one or both of ambiguity and heuristic learning will fail to shift farmers' beliefs to the truth. An education program about how an input or product actually works allows farmers to not rely on heuristics when learning about the input or product; further, an education program could potentially be less expensive than a subsidy program. Efforts should be taken to help reduce noise and ambiguity for those learning about new products in low-income countries. One possible method to improve information quality would be for a village farmer group to record, for each farmer in the village, crops grown on sizes of land, inputs used, farming practices used, yield information, and information on weather, pest, weed, or labor shocks experienced by the farmer. This information, if made available to all farmers in the village, could help to reduce anecdotal information and provide farmers with more information on the actual relationship between inputs and yields experienced in their village. A possible method to improve the usefulness of information is to improve diagnostic tools; like Adhvaryu (2014) showing that correct diagnosis of malaria made it easier to learn about antimalarial medicine efficacy, my results suggest that giving farmers plot-specific fertilizer recommendations can make the signals from their yields more valuable because they will be better reflections of the quality of the fertilizer and not obfuscated by the null or negative effect of the wrong fertilizer.

Chapter 6

Conclusion

This paper presents the results of an incentivized Becker-DeGroot-Marschak auction conducted in Morogoro, Tanzania. I find that rural smallholder farmers' beliefs about the quality of fertilizer in their local market and the certainty of those beliefs have large effects on what they were willing to pay for local urea fertilizer and lab-tested, pure quality urea fertilizer. Farmers who believed that 10 percent more of the fertilizer in their local market was good-quality are willing to pay 3.67% more for local urea fertilizer and willing to pay 4.28% less for lab-tested, pure quality urea fertilizer. On average the willingness-to-pay (WTP) for the lab-tested, pure quality urea fertilizer was 46% higher than local urea fertilizer. This premium disappeared if a farmer thought all the local fertilizer was good-quality. The less a farmer was certain in their belief about local fertilizer quality the more they were willing to pay for lab tested, pure fertilizer; if a farmer did not know and is just guessing about local fertilizer quality they are willing to pay 12.46% more for the lab-tested, pure urea fertilizer. That these beliefs had such substantial effects on farmers' WTP is concerning because evidence shows that all fertilizer in their region is good-quality.

To understand and rationalize these beliefs, I develop a model in which a farmer learns about fertilizer quality. The model has two key features: first, the farmer has multiple priors and second, the farmer misattributes a poor yield to the fertilizer being bad-quality. I simulate the model with and without multiple priors and misattribution to examine the effects of these features on a farmer's beliefs. I compare the effects of different policies designed to increase fertilizer use through simulations. Resolving the ambiguity a farmer faces only moves beliefs 33% closer to the truth when misattribution is present, while removing misattribution from learning leads to beliefs converging to the truth even when ambiguity is present. Policies that address the causes of misattribution (such as an education program) are more successful in shifting a farmer's belief than policies that increase the number of farmers using fertilizer (such as a subsidy) or reduced the number of priors (such as an information campaign on the high quality of fertilizer available in local marketplaces). The number of periods it takes to reach target beliefs increases exponentially as the target belief increases linearly, and the marginal value additional neighbors from which to learn becomes zero after a certain number of farmers are reached.

My results provide new insight into methods and policies to identify, explain, and shift incorrect beliefs. Even so, some limitations should be discussed. Farmers learn about input quality in a noisy environment and face a multitude of signals, so incorrect beliefs could be due to more than just misattribution. In addition, my model makes several simplifications about the learning process that do not reflect real-world learning. One strong simplification is that the farmer's only source of information comes from observing yields; a more realistic situation might also have farmers hear about input quality from neighbors and extension agents, etc. Another simplification is that the farmer is only attentive to the crop yields of farmers who used fertilizer; a more natural process would have the farmer comparing yields of farmers who used fertilizer to those who didn't use fertilizer.

However, my results do demonstrate that misattribution has a strong effect on farmers forming and maintaining incorrect beliefs about input quality. The possibility of sub-optimal learning about new products, in my case fertilizer, is strong in situations where product quality is asymmetric and is more credence than experience, where signals about quality are noisy and ambiguous, and where regulation is limited. Policies intending to increase adoption of new products in these environments, as is the case in many low-income countries, should acknowledge and address possible barriers to learning about the product, like misdiagnosis of antimalarial drugs or oversimplification of the benefits and effects of inorganic fertilizer. Policies including subsidies for or free trials of a good might only experience short-term adoption in situations where users are unable to learn the true benefits of or quality of the good.

Based on my results, policy makers should be wary of overselling technology without frameworks in place to help users understand and use the technology correctly. Overselling technology increases users' expected performance of the technology, which without those frameworks could lead to worse beliefs about the quality of the technology. Trial plots in a village to demonstrate the effects of a new fertilizer on the yield of maize are a possible example. There should not just be a single plot that also has the best quality seed, herbicides, irrigation, and practices. There should be other plots showing the effect of the new fertilizer on different combinations of inputs to show farmers a more realistic representation of what they can expect if *they* use the new fertilizer.

Future research could provide stronger evidence for misattribution and the relationship between incorrect beliefs and input adoption. Extensions to make the model more realistic could include broadening the learning model into an adoption decision model, adding a dynamic income and savings component, and modeling the adoption decision of each village farmer.

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Appendix A

Simulating the Evolution of Beliefs over Time

For a single simulation, I produce two plots that show the evolution of beliefs over time. The first plots (Figures A.1 and A.2) show the distance to the truth for the expectation of each belief over time when there is misattribution and when there is not misattribution. For the plot when there is misattribution, Figure A.1, a belief that is active during a period is bold and inactive during a period is a lighter color. The plot in Figure A.3 helps to show that beliefs that a farmer holds to be inactive and not consider can become taken once again into consideration if they align well with observed data; basically, if yields are particularly bad one year, a farmer could resurrect a belief that inputs are bad-quality. The plot in Figure A.2 shows that when there is not misattribution beliefs quickly converge to the truth.

The second plot (Figures A.3 and A.4) for a single simulation shows the distance between the truth and the mean of the expectation of the active beliefs over time when there is misattribution and when there is no misattribution, respectively; overlaid on the mean is the range between the expectation of the belief furthest from the truth and the belief closest to the truth. The plot in Figure A.3 helps illustrate that even though a farmer might be able to provide a single number representing their beliefs (i.e., "I think that 80% is good"), what they consider to

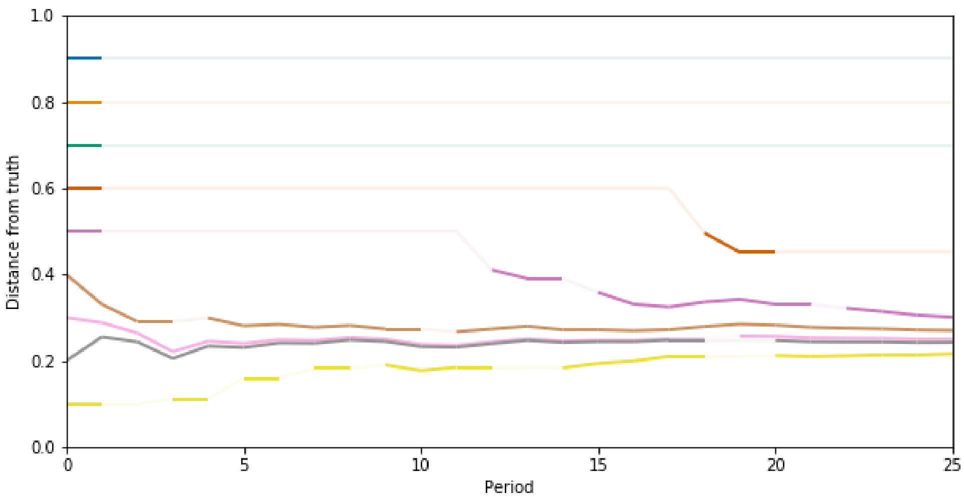

Figure A.1: Plot of the evolution of the distance to the truth of each of a farmer's beliefs for a single simulation when there is misattribution. If a belief is active in a certain period it is bold, while if it is inactive is it faded out.

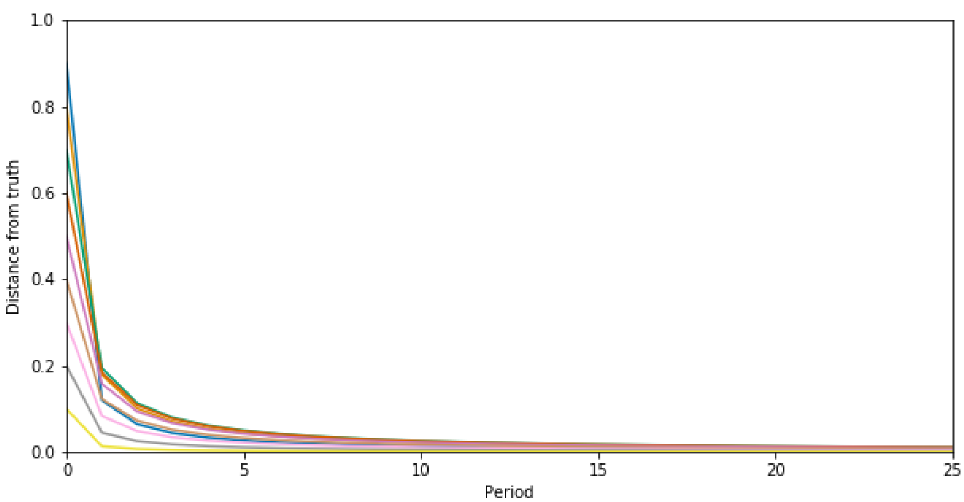

Figure A.2: Plot of the evolution of the distance to the truth of each of a farmer's beliefs for a single simulation when there is no misattribution.

be possible could encompass much more than that single number. Also illustrated by this plot is the effect of the inactive priors becoming active due to randomness in yields and misattribution: the mean gets much worse and the range of possible beliefs increase considerably. Figure A.4 shows how the range of possible beliefs decreases monotonically quickly when there is no misattribution.

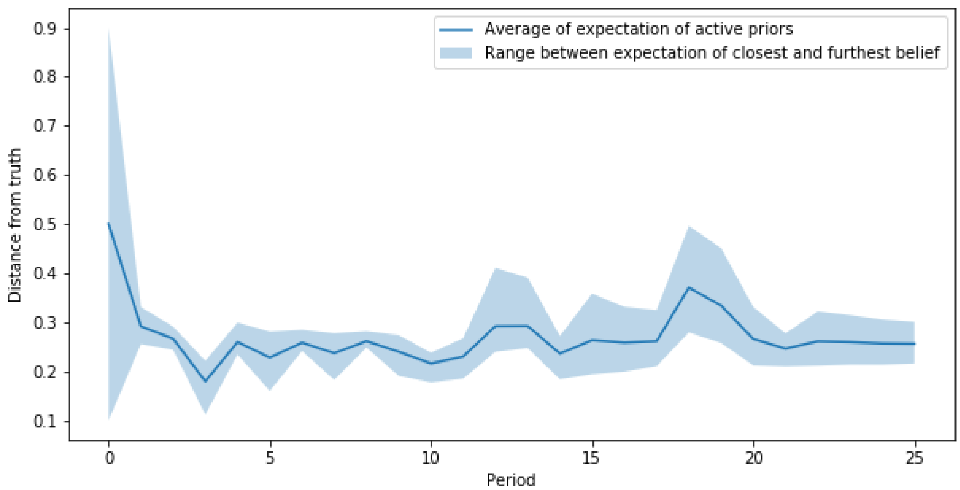

Figure A.3: Plot of the evolution of the distance to the truth of each of a farmer's beliefs for a single simulation when there is misattribution. If a belief is active in a certain period it is bold, while if it is inactive is it faded out.

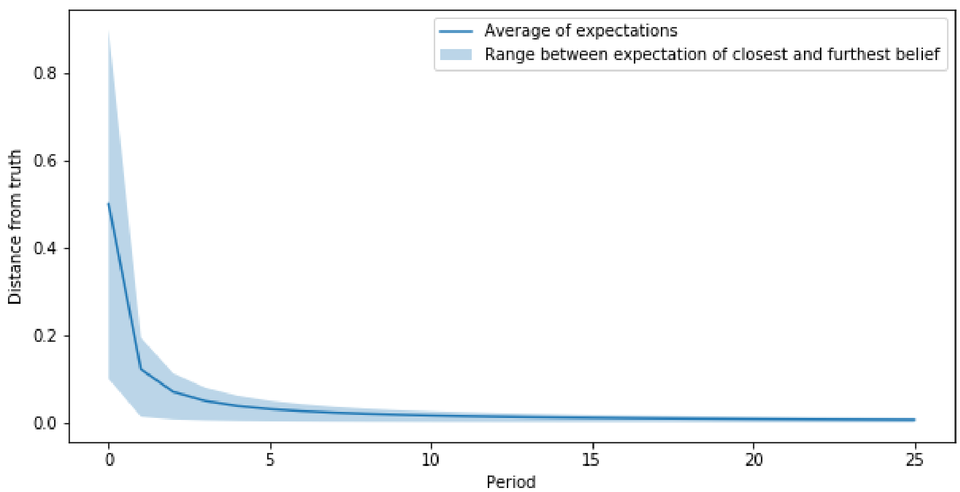

Figure A.4: Plot of the evolution of the distance to the truth of each of a farmer's beliefs for a single simulation when there is no misattribution.