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LEMON TECHNOLOGIES AND ADOPTION: MEASUREMENT, THEORY, AND EVIDENCE FROM AGRICULTURAL MARKETS IN UGANDA*

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To reduce poverty and food insecurity in Africa requires raising productivity in agriculture. Systematic use of fertilizer and hybrid seed is a pathway to increased productivity, but adoption of these technologies remains low. We investigate whether the quality of agricultural inputs can help explain low take-up. Testing modern products purchased in local markets, we find that 30% of nutrient is missing in fertilizer, and hybrid maize seed is estimated to contain less than 50% authentic seeds. We document that such low quality results in low average returns. If authentic technologies replaced these low-quality products, however, average returns are high. To rationalize the findings, we calibrate a learning model using data from our agricultural trials. Because agricultural yields are noisy, farmers' ability to learn about quality is limited and this can help explain the low quality equilibrium we observe, but also why the market has not fully collapsed.
JEL Codes: D83, L15, O13, O33, Q12.

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I. Introduction

Over the past half century, agriculture in Sub-Saharan Africa has failed to experience any significant productivity improvements (Evenson and Gollin 2003). This is broadly viewed as a central reason the region has not embarked on a path of sustained economic growth and mass poverty is still widespread. Low use of modern, but simple technologies, including fertilizers and hybrid seeds, is often suggested as an explanation for why agricultural productivity has remained stagnant, but why adoption rates are so low still remains somewhat of a mystery (see reviews in Foster and Rosenzweig 2010; Jack 2011, for example).

A number of promising and potentially interlinked explanations have been put forward in recent literature, including missing markets for risk and credit (Karlan et al. 2014), lack of knowledge and behavioral constraints (Duflo, Kremer, and Robinson 2006, 2011), and uncertainty (Suri 2011). In this article, we investigate a complementary explanation that takes its starting point in the technology itself: the quality of the technology as provided in the market. This investigation provides the first large-scale empirical assessment of the prevalence of poor-quality technologies (fertilizer and hybrid seed) in local markets in Africa and its implications for economic returns to adoption. To this end, we combine data from laboratory tests with data from researcher-managed agricultural trials. We complement the objectively measured quality data with information on farmers' beliefs about the quality of inputs in the market and their beliefs about the expected yield returns of using either authentic or market-based inputs.

We establish that low-quality inputs are rife in the local retail markets we surveyed. Specifically, we find that 30% of nutrient is missing in fertilizer, and hybrid maize seed is estimated to contain less than 50% authentic seeds. Moreover, we document that such low quality results in close to zero average rates of return in our baseline specification. If authentic technologies replaced these low-quality products, however, average returns for smallholder farmers would be over 80%. Together these results suggest that one reason smallholder farmers do not adopt fertilizer and hybrid seed is that the technologies available in local markets are simply of too low quality to be profitable.

We use our data to rationalize the results we document. Specifically, the data show not only low average fertilizer quality but substantial heterogeneity in quality, which is not correlated with price. This suggests that farmers' ability to infer quality may

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be severely limited, since we would otherwise expect prices to adjust (Shapiro 1982; Mailath and Samuelson 2001). To investigate this further, we exploit data from our agricultural trials. The experimental data provide estimates of average yield conditional on quality and an estimate of the whole density of yields for a given quality. We use these data and calibrate a simple Bayesian learning model to show that farmers experimenting on small plots will quickly be able to infer that the quality of fertilizer is low if the level of dilution of the fertilizer is sufficiently high.[1] Consistent with this finding, we find few samples with very low quality in the market place. However, for almost the full range of substandard inputs we observe in the market, we estimate that most farmers in the model, even after several periods of experimentation, would not gather enough information to confidently conclude that bad-quality products are sold, when that is in fact the case. On average, the Bayesian farmers' willingness to pay for fertilizers with market quality is also low, although there will be some farmers who, after observing high yield from relatively low-quality inputs in a small number of experiments, end up with a willingness to pay equal to or above the average market price. This result can help explain the low but positive average adoption rate we observe in the data. Our findings also help explain why we do not observe sellers selling high-quality products at a premium price: the pecuniary incentives to build up and maintain a high-quality reputation, given the beliefs of the farmers we surveyed, simply appear too weak. We argue, however, that by lifting some of the constraints to adoption that have been highlighted in the recent literature, one could, through the improved learning environment that would likely follow, create stronger incentives for a high-quality seller to enter the market.

The article is structured as follows. In Section II we briefly describe the context. Section III describes the data. Section IV presents the main findings on the quality of the technologies available in the market. In Section V we estimate the returns

1. Our modeling setup is related to other work on technology adoption in agriculture. In Foster and Rosenzweig (1995) and Conley and Udry (2010), farmers learn about the optimal level of fertilizers (with a fixed quality) to be applied. Besley and Case (1994) and Munshi (2004) present models where farmers learn about the expected yield when applying fertilizers (of a fixed quality). Hanna, Mullainathan, and Schwartzstein (2014) examine a learning model in which farmers do not pay attention to certain dimensions of the production function. In contrast, the Bayesian farmer here learns about the quality of the technology itself.

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to adoption, and in Section VI we present results on farmers' beliefs about quality in the market and their expectation of yields conditional on quality. In Section VII, we rationalize the observed low-quality equilibrium by developing a parsimonious Bayesian learning model and use data from the agricultural trials to quantify farmers' ability to learn, and their willingness to pay, from small-scale experimentation. Section VIII concludes with a discussion of the implications of our findings.

II. Context

The agriculture sector in Uganda, as in most countries in the region, is dominated by smallholder farmers, a majority of which cultivate less than two hectares. Maize is the most widely cultivated crop and is grown throughout the country, often on soil with low fertility.[2]

Data on smallholder farmers' technology use (fertilizer and hybrid seeds) in Africa are sketchy. The World Development Indicators, using data collected by the Food and Agriculture Organization (FAO), report average fertilizer consumption (kilograms per hectare of arable land) for a large set of Sub-Saharan African countries. However, since large-scale commercial farms and agricultural producers consume a large fraction of the total, these averages typically do not provide an accurate measure of smallholder farmers' use.[3]

Nationally representative household surveys with a focus on agriculture exist for some countries. The LSMS Integrated Surveys on Agriculture program, for example, has collected panel data for eight Sub-Saharan African countries, including Uganda. Online Appendix Table A.1 extends and updates Sheahan and Barrett's (2014) estimates of overall national fertilizer and improved seed use statistics using the latest rounds of LSMS data. Based on data for 2012/2013, we estimate that 7% of cultivating households in Uganda, and almost 1 in 10 households growing maize, used some type of fertilizer in the last year. Twenty-two

2. Declining soil fertility has been highlighted as a key concern in Sub-Saharan Africa, including Uganda (Sanchez 2002; Nkonya, Kaizzi, and Pender 2005).

3. For example, average fertilizer consumption in Mozambique was approximately four times higher than in Uganda in 2013 (World Bank 2016), but only 3% of imported fertilizer was used for food crops, and only a fraction of this was used by smallholder farmers. Fifty percent of the imported fertilizer was used by a multinational tobacco producer (World Bank 2012).

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percent of cultivating farmers report planting improved seeds on at least one of their plots.[4] There are large variations in input use across Uganda's four regions, with very low usage of fertilizer and improved seed in the northern region, while 13% of cultivating maize-growing households report using fertilizers, and 27% report using improved seeds, in the main maize-growing region.

Adoption rates are higher for fertilizers but more similar for improved seeds in the other seven countries surveyed by the LSMS (see Online Appendix Table A.1), with the share of households using some inorganic fertilizers varying from 15% (in Tanzania) to 78% (in Malawi), and the share of households using some improved seeds varying from 15% (in Niger) to 49% (in Malawi).

Most Sub-Saharan African countries, as is the case for Uganda, import fertilizers, but a significant fraction of the hybrid seeds in the market are produced domestically. In Uganda, large commercial farms and agricultural producers source fertilizers directly through international sources, or through one of the approximately 10 importers, many of whom also act as domestic distributors or wholesalers, and buy hybrid seeds directly from national seed companies or from importers linked to international seed producers (IFDC 2014). There is also a larger set of wholesalers/retailers in the market, which do not import inputs themselves, from which local agro-input retail shops typically source.

Ugandan supply costs mirror those documented for farmers in Kenya and Tanzania, but Ugandan farmers face higher transport costs due to longer distances and border-related constraints (IFDC 2014). In addition, and unlike most countries on the continent, Uganda does not have a national fertilizer subsidy program, which is probably one important explanation for the relatively low average fertilizer use.[5] Uganda differs from several other African countries in that there is no state participation in import and distribution of fertilizers and hybrid seeds.

In local retail stores, hybrid seeds and fertilizer are usually sold in smaller packages which the retailer has repacked from larger bags. Most fertilizers are sold under their generic name

4. Improved seeds are either open pollinated variety (OPV) seeds or hybrid seeds.

5. Many African countries have a subsidy program for fertilizer, and some have a program for hybrid seeds. There are large differences in how these programs work and the extent of the subsidy across countries. The most generous program is in Malawi, where participating farmers receive a subsidy up to 90% for both fertilizers and seeds (IFDC 2013).

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(urea, DAP, NKP, for example), and hybrid seeds (when in large bags) typically are branded with names specifying the seed producer and type of seed.

Concerns about poor-quality inputs in the agricultural sector are neither new nor specific to Uganda. In fact, addressing poor-quality inputs through the strengthening of the regulatory enforcement capacity and the capacity for quality assurance was listed as one of the main policy recommendations in a recent USAID-funded review of fertilizer markets in 12 Sub-Saharan African countries (IFDC 2015).

Low-quality inputs could be due to a multitude of factors, including adulteration, poor storage, and inappropriate handling procedures. Moreover, quality deterioration could manifest at different points in the supply chain. There are news reports and anecdotal evidence from many African countries about adulteration of both seeds, fertilizers, and other agro-inputs, such as pesticides, at different parts of the supply chain, including the importation of diluted inputs, the bulking out of fertilizer, or dyeing simple grain to look like hybrid seeds by wholesalers. Although news reports across the region have primarily focused on adulteration scandals at the higher end of the supply chain, anecdotal evidence suggests that adulteration also takes place at the retail level, where larger bags are repacked into smaller ones. The repacking and the open-air storage of larger bags in retail stores can lead to dilution of key nutrients in fertilizer and lower the quality of hybrid seeds.

III. Data and Measurement

We investigate the quality of one of the most popular high-yield variety of maize seed in the Ugandan market and a generic nitrogen-based fertilizer (urea). Nitrogen has been shown to be the main limiting nutritional component to maize growth in Uganda (Kaizzi et al. 2012).

To measure the quality of the technologies in the market, we combine data on the nitrogen content of fertilizer from retail shops and experimental yield data from our own agricultural trials.

At 129 randomly sampled local retail shops in two of the main maize-growing regions of Uganda, we purchased 369 samples of urea fertilizer ("retail fertilizer"), and at 30 such shops we purchased 30 samples of branded hybrid seed of the predetermined type ("retail hybrid seed"), using a mystery shopper approach (see Online Appendix for details). We also purchased urea and hybrid seed in bulk directly from one of the main wholesalers for

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urea ("authentic fertilizer") and the seed company producing the branded seed ("authentic hybrid seed"). Finally, we purchased traditional farmer seed from a random sample of 80 small-scale maize farmers living around the trading centers where hybrid seed was purchased.

Each retail fertilizer sample was tested three times for the content of nitrogen (N) using the Kjeldahl method (Anderson and Ingram 1993) at the Kawanda Agricultural Research Institute laboratory. We used the mean of these tests to determine the quality of a sample. Authentic urea should contain 46% nitrogen (%N) and we confirmed this to be the case in our authentic sample.

Researcher-managed agricultural trials at five of the National Agricultural Research Laboratories' research stations across Uganda were used to determine the yield responses of fertilizer and estimate the quality of hybrid seed sold in retail markets. Authentic urea was diluted by proportionately adding acid-washed sand to get urea samples with 75% of stated N (approximately 34%N), 50% of stated N (approximately 23%N), and 25% of stated N (approximately 11%N). Together with authentic urea (46%N) and no urea, this yields five fertilizer treatments (N = 46%; N = 34%; N = 23%; N = 11%; N = 0%). We combined the five fertilizer treatments with the three seed treatments (authentic hybrid seed, retail hybrid seed, and farmer seed) to yield 15 possible seed-fertilizer quality combinations that were randomly assigned six 30 m^2 plots each at each of the five experimental sites. In total, each treatment combination was grown 30 times, and yield data were collected from 450 plots.

The crop management and data collection protocol (see Online Appendix for details) followed the methodology outlined in Kaizzi et al. (2012). All five sites were managed by the research team, and the staff assigned to implement the trial protocol were blinded to the treatment status of the plots. We planted two maize seeds per hill with a spacing of 30 × 75 cm between hills, for a total of 105 hills per plot. We applied fertilizer at 108 kg per hectare (which corresponds to the official recommendation of 50 kg N/ha for authentic urea) in two splits: half at planting by broadcasting and immediately incorporating into the soil and half later at tasselling top dress. In harvesting, we excluded the outer perimeter of the plot, and we oven-dried the grains to correct for moisture.

Unlike the content quality of fertilizers, which can be tested directly in a laboratory, we infer the quality of retail hybrid seeds by focusing on their yield response. Intuitively, we assess the quality by assuming the following: if a bag of farmer seed yields X tons

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TABLE I
PERCENT NITROGEN (%N) IN RETAIL FERTILIZERS (UREA)

	Mean	Standard deviation	Minimum	Maximum	Observations
%N	31.8	5.7	8.1	44.3	369

Notes. Summary statistics on the nitrogen content of the 369 fertilizer samples purchased in the covert shopper exercise and analyzed in the laboratory.

of maize, a bag of authentic hybrid seed yields Y tons of maize and a bag of retail hybrid seed yields $\alpha X + (1 - \alpha)Y$ tons of maize, then the bag of retail hybrid seed is of the same quality as a bag of authentic hybrid seed that is diluted with α% farmer seed.

More formally, we first match the experimental yield data for the three types of seed by site, block, and nitrogen content of the fertilizer applied. Then we construct a new variable in each strata, which is the weighted sum of the average maize yield on the plots growing farmer seed in stratum s and the average maize yield on the plots growing authentic hybrid seed in stratum s: $Yield_{s,mix} = \alpha Yield_{s,farmer} + (1 - \alpha)Yield_{s,authentic}$. Third, we calculate the first four central moments of this new variable and of the distribution of yields on plots growing retail hybrid seed—the latter also averaged over the plots in each stratum. Finally, we infer the most likely level of dilution by finding α that minimizes the squared weighted difference between the simulated moments and the data moments (see Online Appendix for details).

We complement the data on the quality of the technology with household survey data, administered to 312 small-scale farmers (farmers with farms of two hectares or less) residing around the trading centers visited as part of the fertilizer quality study. The household survey collected detailed data on farmers' agricultural practices, including input use and market interactions, and their expectations about the quality of and yield return to fertilizers (see Online Appendix for details).

IV. THE QUALITY OF THE TECHNOLOGY

As reported in Table I and illustrated in Figure I, on average, retail fertilizer contained 31% less nutrient than authentic fertilizer or 31.8% N per kilogram (95% CI: 31.3–32.4). Defining fertilizer dilution in sample j, d_j, as $d_j = \frac{(46 - \%N_j)}{46}$, we find no fully authentic fertilizers and less than 1% with a dilution level (d_j) less than 10%. We also observe very few highly diluted samples

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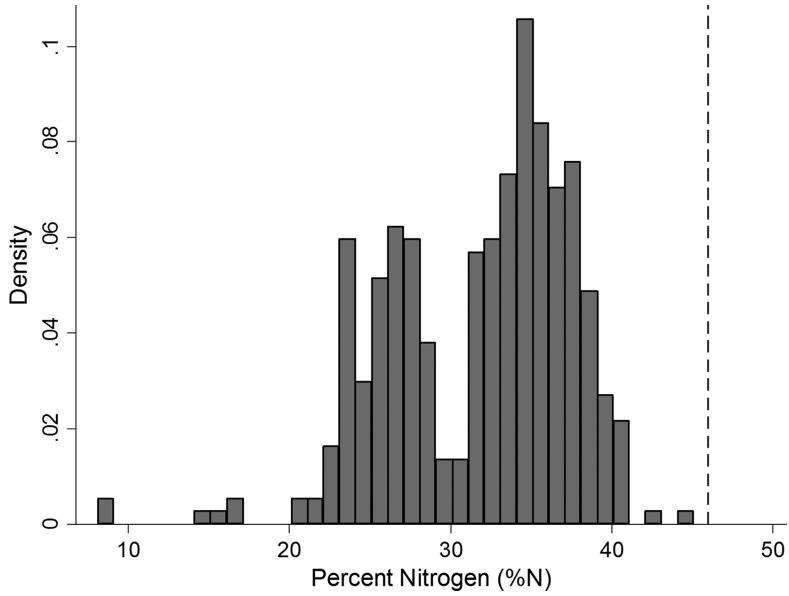

FIGURE I

The Distribution of Nitrogen Content in Fertilizer

The bars present the percentage of the 369 fertilizer samples with nitrogen content equal to the values shown on the *x*-axis. The dashed vertical line indicates the amount of nitrogen in authentic fertilizer. Data from the covert shopper survey, with percent nitrogen (%N) tested in the lab.

(4% of the samples are diluted by more than 50%). In other words, the large majority of samples (95%) have low to moderate dilution levels (ranging from 10% to 50%).[6]

Figure II shows that although there was substantial variation in quality across samples, prices were largely homogeneous.

Figure III links quality of the inputs to yields and shows that shortfalls in quality reduce yields substantially. For example, average yield is approximately 40% higher when using authentic inputs (fertilizer and hybrid seeds) than when using inputs with average retail quality.

Columns (1)–(3) in Table II report estimates of linear regressions of yield on nitrogen content (%N) when planting

6. In a follow-up study (see Online Appendix for details) we show that dilution of fertilizers is not specific to urea. A test of 126 samples of DAP (a multinutrient fertilizer with nitrogen and phosphorus as the main nutrients) shows an average dilution level of 25.9%, ranging from essentially 0% to 91% dilution.

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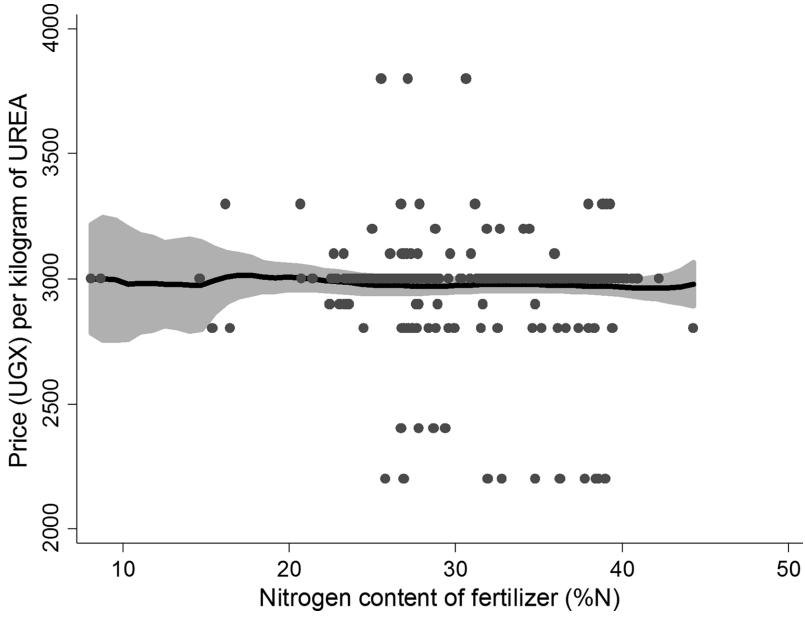

FIGURE II

The Relationship between Price and Quality of Fertilizer

The dots show the combination of nitrogen content and price per kilogram of urea for the 369 fertilizer samples. The solid line is based on a local polynomial regression fitted to the data, and the gray shaded area represents the 95% confidence interval. Data from the covert shopper survey with percent nitrogen (%N) tested in the lab.

either farmer seed, retail hybrid seed, or authentic hybrid seed. A reduction of nitrogen by 1 percentage point when planting traditional farmer seed leads to a significant yield loss of 49 kg per ha ($p < .001$, t test). The loss due to poor quality is even higher when planting retail hybrid seed (57 kg/ha, $p < .001$, t test) and the highest when planting authentic hybrid seed (65 kg/ha, $p < .001$, t test). For the fertilizer ranges considered here, the quality of the technology is approximately linearly related to yield as graphically illustrated in Figure IV, using a nonparametric Fan local regression method.[7]

7. It is well established that at higher levels of fertilizer application the marginal yield return to (nitrogen-based) fertilizers is falling in the amount of fertilizer applied (see for example Duflo, Kremer, and Robinson 2008; Wortmann et al. 2011; Kaizzi et al. 2012). Here we consider the lower end of

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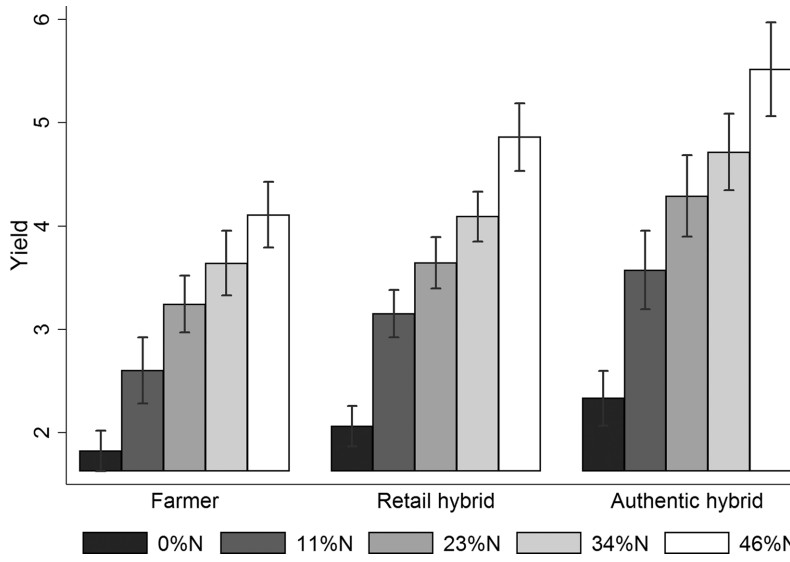

FIGURE III

The Yield Return to Nitrogen Content in Fertilizer

The bars present maize yield in metric tons per hectare growing farmer seed (left panel), retail hybrid seed (middle panel), and authentic hybrid seed (right panel) after applying fertilizer with percent nitrogen (%N) given by 0%N, 11%N, 23%N, 34%N or 46%N. The error bars represent the 95% confidence interval. The unit of observation is an experimental plot. Data from the experimental plots.

The results of the simulated moments estimation on retail seed quality are presented in Table III. The simulated method of moments estimate for α is 0.52 (95% CI: 0.30–0.74). From this we conclude that the average quality of a bag of retail hybrid seed is roughly the same as the quality of a bag mixed 50-50 with farmer seed and authentic hybrid seed. Figure A.1, in the Online Appendix, plots the cumulative distribution function (CDF) of retail hybrid seeds and the distribution generated by mixing farmer (52%) and authentic hybrid seeds (48%). The two curves lie almost on top of each other and a Kolmogorov-Smirnov test confirms that we cannot reject the null hypothesis that the two distributions are equal (p-value = .90).

the relationship between applied nitrogen and yield for which there is little experimental evidence.

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TABLE II

YIELD RETURN (METRIC TONS PER HECTARE) TO INCREASING QUALITY OF FERTILIZERS

Sample	Experimental sites			Farmer survey
Specification	(1)	(2)	(3)	(4)
%N	0.049***	0.057***	0.065***	
	(0.004)	(0.004)	(0.005)	
Expected %N				0.060**
				(0.024)
Constant	1.973***	2.268***	2.600***	0.82
	(0.095)	(0.087)	(0.126)	(0.56)
Observations	150	150	150	292
R-squared	0.52	0.65	0.52	0.02
Seeds	Farmer	Hybrid market	Hybrid authentic	Farmer
Unit of analysis	Plots	Plots	Plots	Farmers

Notes. Values shown are coefficients from ordinary least squares regression. Each column represents a different regression. The dependent variable in columns (1)–(3) is maize yield (metric tons per hectare) on experimental plots. The independent variable is content of nitrogen (percent nitrogen; %N) in the fertilizer applied to the experimental plot. The dependent variable in column (4) is expected maize yield (metric tons per hectare) based on farmer survey data, and the independent variable is expected content of nitrogen (percent nitrogen; %N) in the nearest retail shop. The p-value on the test of the null hypothesis that the coefficients in specifications (1) and (2) [(1) and (3)] {(2) and (3)} are equal is 0.00 [0.02] {0.02}. Robust standard errors in parentheses. *** 1% , ** 5% , * 10% significance.

V. THE ECONOMIC RETURNS TO TECHNOLOGY

Having established that modern technologies available in local retail markets are of poor and heterogeneous quality, we examine how quality affects the returns to adoption of retail hybrid seed and retail fertilizer. The unit of observation for these calculations is a retail fertilizer sample.

The net return of a fertilizer sample j with nitrogen content n_j (%N) applied to retail hybrid seed is the difference between the revenue from planting retail hybrid seed with retail fertilizer—minus the direct and additional labor costs associated with the inputs—and the revenue from planting traditional seed with no fertilizer. The rate of return of adopting fertilizer and hybrid seed is given by dividing the net return by the total cost of adoption. A fertilizer sample is deemed profitable if its rate of return is greater than 0.

Predicted yield for a given seed type and fertilizer quality can be derived from Table II. Specifically, let s_k denote seed type, with s_1 being farmer seed, s_2 being retail hybrid seed, and s_3 being authentic hybrid seed. The predicted yield of a fertilizer sample

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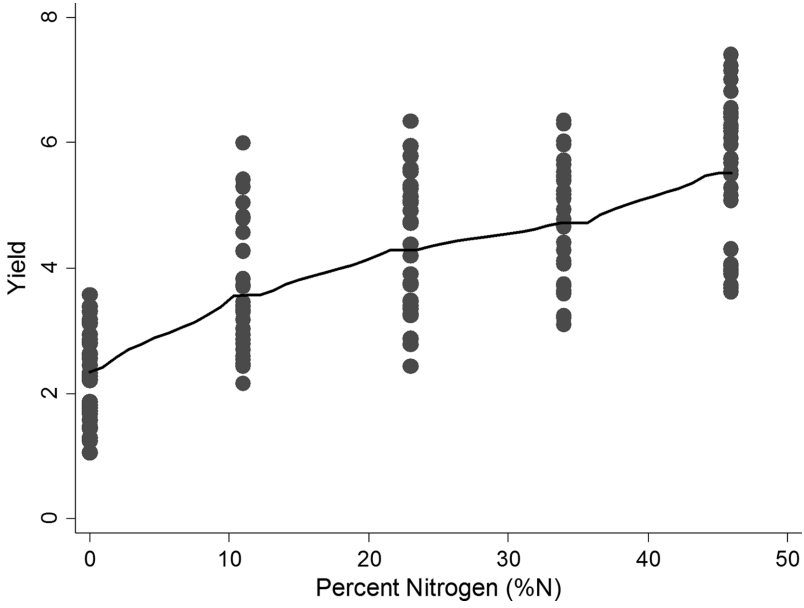

FIGURE IV

The Yield Return to Increasing Quality of Fertilizers

Nonparametric Fan regression of yield (metric tons per hectare) on percent nitrogen (%N) in fertilizers with authentic seeds. The unit of observation is an experimental plot. Data from the experimental plots.

with nitrogen content n_j %N using seed type s_k is $\hat{y}(n_j, s_k) = \hat{\alpha}_k + \hat{\beta}_k \times n_j$ where the subscript k on the estimated coefficients refers to the column number in Table II.

The predicted net return (NR) of a fertilizer sample j with nitrogen content n_j %N, using retail hybrid seed, is calculated as

$$NR(n_j, s_2) = p^m \hat{y}(n_j, s_2) - c_j^f - c^s - l^{fs} - p^m \hat{y}(0, s_1), \quad (1)$$

where p^m denotes the market price of maize (per metric tons), c_j^f and c^s are the costs of fertilizer and seed per hectare, and l^{fs} is the additional labor cost per hectare of land; that is, the complementary input responses due to adoption of hybrid seeds and fertilizers. $p^m \hat{y}(n_j, s_2)$ is the predicted revenue per hectare of land, using the results in Table II, column (2), to predict $\hat{y}(n_j, s_2)$. $p^m \hat{y}(0, s_1)$ is the revenue from traditional farming (no hybrid seed

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TABLE III
ESTIMATES OF QUALITY OF RETAIL HYBRID SEED BASED ON ITS YIELD

	Retail hybrid seeds (1)	Mix of authentic and farmer seeds (2)
α		0.52
		(0.11)
Mean	3.563	3.566
Variance	1.172	1.264
Skewness	–0.058	–0.069
Kurtosis	2.437	2.123
Criterion value		1.63

Notes. The unit of observation is a stratum, which contains the plots that are on the same site and block and have fertilizer with the same level of nitrogen applied to them. Column (1) contains the first four moments from the observed distribution of yields (metric tons per hectare) planting retail hybrid seed averaged at the stratum level. Column (2) presents the estimate of α that minimizes the squared weighted distance between the first four moments of this distribution and a simulated distribution of yields constructed by combining the maize yield from plots growing farmer seed and the maize yield from plots growing authentic hybrid seed in each stratum using the ratio $\alpha : 1 - \alpha$. The first four moments of this simulated distribution and the value of the criterion at the estimated α are reported. Standard errors in parentheses are bootstrapped drawing 1,000 samples from the yield distribution.

or fertilizer), where the predicted yield is estimated from Table II, column (1).

To calculate the predicted NR for authentic inputs, we replace n_j with $n = 46$ and s_2 with s_3 in equation (1). Note that the variation in NRs for inputs bought in local markets is driven by variation in nitrogen content (n_j), and thus expected yield, and the cost of the fertilizer (c_j^f), whereas the variation in NRs for authentic inputs is driven by differences in costs only.

To estimate the net returns we need data on the output price (p^m), input costs (c_j^f, c^s), and the cost of complementary labor inputs (l^{fs}).

The market price for maize per hectare (p^m) is estimated from the farmer survey where we collected information on the value and amount of harvest sold in the last season. From this we derive the price each farmer received. Since the reported output price is strongly left-skewed, we used the median (UGX 500,000 or US$170 per metric tons) rather than the mean price.[8]

8. The market price for maize varies over the season (see, for example, Burke 2014). We did not collect data on the timing of the sale. However, due to inadequate on-farm storage, most smallholders are forced to sell their produce at harvest when prices are considerably lower. The estimated farm-gate price of UGX 500/kg is consistent with other data. For example, the Famine Early Warning Systems

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TABLE IV
COMPLEMENTARY LABOR INPUTS

	Family labor (days) (1)	Family labor (days) (2)	Expenses on hired labor (3)	Expenses on hired labor (4)
Using fertilizer	32.4	10.2	197,566*	127,875*
	(24.5)	(17.1)	(101,310)	(67,091)
Using improved seeds	1.52	–3.58	119,267***	103,220**
	(12.5)	(11.6)	(38,660)	(40,231)
Using fertilizer & improved seeds		30.7		96,708
		(28.7)		(136,274)
Constant	105.7***	107.7***	70,288**	76,739*
	(9.6)	(8.7)	(32,922)	(28,409)
p-value: *F*-test (fertilizer, seeds)	0.37	0.69	0.02	0.04
Observations	312	312	310	310

Notes. Labor inputs conditional on technology adoption. Unit of observation is a household. OLS estimates from a linear regression with location (trading center) fixed effects. Improved seeds are either open-pollinated varieties (OPV) or hybrid seeds. Family labor is adult labor days per season, with working day normalized to eight hours. Expenses on hired labor per hectare in Ugandan shillings per season, UGX (exchange rate was approximately UGX 3,200 = US$1). *F*-test is the test of the null hypothesis ($\beta_{Fertilizer} = 0$ and $\beta_{Seed} = 0$). Standard errors clustered by location (trading center) are in parentheses. *** 1% , ** 5% , * 10% significance.

The price of each fertilizer sample and the average (and the median) price for the hybrid seed were collected as part of the covert shopper surveys. The costs of fertilizer and seed, c_j^f and c^s, are then calculated assuming that inputs were applied using the officially recommended amounts per hectare.

Estimating the complementary labor response due to adoption is more problematic, as this choice is obviously endogenous. As a reference, Beaman et al. (2013) use an experimental design to estimate the change in complementary input use, including family and hired labor, in response to free provision of fertilizers. They do not observe any change in the amount of family labor used but an increase in hired labor, and estimate that the total complementary input expenses (excluding fertilizers) account for 26% of total input expenses (including the cost of fertilizers used) for the treatment group receiving the full fertilizer treatment.

Table IV reports the results from regressing family labor and expenses on hired labor on fertilizer and hybrid seed application,

Network report retail prices of maize in one of the main markets in the western region of Uganda. At the time of harvest in 2013, the retail price was UGX 600/kg. Since this is the retail price in one of the larger market centers, it provides an upper bound of the average farm-gate price.

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using data from the smallholder farmers we surveyed. In our sample, 21% of the farmers use some type of fertilizer and half use improved maize seeds (OPV or hybrid seeds).[9] As in Beaman et al. (2013), adoption of improved seeds and/or fertilizers is not associated with a significant change in the amount of family labor applied, but increased expenses on hired labor. Our nonexperimental estimates, evaluated at the mean of fertilizer and hybrid seed costs (c_j^f, c^s), column (3), imply that the complementary expenses for hired labor (l^{fs}) account for 32% of the total input expenses ($c_j^f + c^s + l^{fs}$) for farmers using fertilizers and improved seeds. Although these estimates are close to Beaman et al.'s (2013) experimental estimates, they are not causal estimates, so to check the robustness of the findings we also impute rates of return assuming the complementary labor expenses are 25% or 50% less than those reported in Table IV.

Low quality of inputs in the market reduces the economic returns to adoption substantially. As Table V, Panel A, shows, using retail fertilizer and retail hybrid seed yields very low returns on average (mean $r = 6.5\%$ and median $r = 10.8\%$). In contrast, if authentic technologies were sold in local retail stores, the mean and median rate of return would be close to 80%. Although 65.6% of the fertilizer samples bought in local markets yield positive returns, only 8.9% yield a return above 25% and none over 50%; two thresholds that are likely to be more relevant given market interest rates of 20–25%. If all samples had been authentic, 99% of the samples would have yielded a return above 70%.[10]

In Table V, Panel B, we reestimate the returns assuming the costs of the complementary inputs are 25% lower than in the baseline scenario reported in Panel A, and in Panel C, we report rates of return of adoption assuming the costs of the comple-

9. In the research-managed trials, urea was used both at planting and for top dressing. It is not uncommon, however, for farmers using fertilizers to use different types of fertilizers at planting and for top dressing. It is therefore more accurate to use a more aggregate measure of fertilizer use, rather than adoption of a specific type of fertilizer.

10. For single-nutrient fertilizers, like urea, given observed dilution levels, the rates of return would initially tend to increase if farmers use more than the recommended dosage. Overdosing, however, may be less beneficial when applying a multinutrient fertilizer (as the relative magnitudes of the main nutrients matter and diluted multinutrient fertilizer may not have the same relative amounts of the main nutrients as authentic fertilizers) and would not be a viable option for diluted seeds.

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TABLE V

ECONOMIC RETURNS TO FERTILIZER AND HYBRID SEEDS ADOPTION

Source	Technologies available in the market (1)	Authentic technologies (2)
Panel A: Adoption of UREA fertilizers and hybrid seeds		
Mean rate of return	6.5%	83.6%
Median rate of return	10.8%	83.1%
Fertilizer samples yielding positive net return	65.6%	100.0%
Fertilizer samples yielding rate of return > 25%	8.9%	100.0%
Fertilizer samples yielding rate of return > 50%	0.0%	100.0%
Panel B: 25% lower complementary expenses		
Mean rate of return	15.8%	99.6%
Median rate of return	20.5%	99.0%
Fertilizer samples yielding positive net return	76.7%	100.0%
Fertilizer samples yielding rate of return > 25%	37.1%	100.0%
Fertilizer samples yielding rate of return > 50%	1.1%	100.0%
Panel C: 50% lower complementary expenses		
Mean rate of return	26.9%	118.7%
Median rate of return	31.9%	117.9%
Fertilizer samples yielding positive net return	89.2%	100.0%
Fertilizer samples yielding rate of return > 25%	62.3%	100.0%
Fertilizer samples yielding rate of return > 50%	7.9%	100.0%

Notes. Average and median rate of return, and threshold values, for adopting fertilizer and hybrid seed on one hectare of land. The unit of observation is a fertilizer sample. Column (1) presents the rate of return of technologies available in the market and column (2) presents the rate of return if technologies were authentic. Panel A, baseline scenario (see text for details). Panel B reports returns assuming 25% lower complementary labor expenses and Panel C reports returns assuming 50% lower complementary labor expenses compared to the baseline scenario reported in Panel A.

mentary inputs are 50% lower. Twenty-five percent lower costs of complementary inputs imply the same cost share, $\frac{l^{fs}}{(c^f+c^s+l^{fs})}$, on average, as in Beaman et al. (2013); that is, 26%, while 50% lower expenses on complementary inputs imply that the complementary inputs (here, hired labor) account for less than one-fifth of the total expenses for adoption.

With 25% lower complementary input expenses (Panel B), the mean rate of return of inputs purchased in local markets is 15.8% compared with 99.6% had these inputs been of authentic quality. Of the samples bought in local markets, 37.2 would yield a return above 25%, but a mere 1.1% would yield a return above 50%. With 50% lower complementary input expenses, more than half of the samples yield a return above 25%, but still only 7.9% yield

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a return above 50%. As a comparison, for authentic technologies, almost all yield a return over 100%.

Our results are also robust along a number of other dimensions. The economic returns reported in Table V were derived from the experiments run on researcher-managed agricultural stations. The experimental fields were chosen to mimic the agricultural conditions faced by many smallholder farmers in Africa—and soil tests confirmed that that was indeed the case.[11] It is still likely, however, that the yields (and thus the returns) we estimate are higher than most small-scale farmers would achieve because the crop management (planting, weeding, harvesting, etc.) followed recommended practice and the procedures were homogeneously applied across all plots. Many farmers, to a varying degree, do not consistently follow these recommended guidelines. An advantage of our approach is that the variation across plots and mean outcomes are not driven by farmer-specific factors. We exploit that variation in Section VII when we try to rationalize the observed equilibrium in the market. Importantly, it also helps us interpret the findings we report in Table V: the estimates provide upper bounds—both for market and authentic technologies—on the return to adoption. That is, we estimate the returns that a smallholder farmer with up-to-date knowledge about crop management should be able to achieve.

Poor crop management would lower yields and thus returns and would therefore make adoption of inputs bought in local markets even less likely to be profitable.[12] To illustrate the effects, assume yields are $\varphi\hat{y}(n_j, s_k)$, where $\varphi > 0$. Online Appendix Figure A.2 plots the mean rate of returns for retail and authentic technologies for different values of φ. As an example, if estimated yields are 20% lower ($\varphi = 0.80$) than in the baseline scenario reported in Table V, Panel A, the mean return is –15% for

11. See Online Appendix, section A.2 for details.

12. We estimate that average yield for small-scale maize farmers using traditional technologies (traditional seeds and no fertilizers) in 2013, using data from the 2013/2014 LSMS data for Uganda, was 1.57 metric ton per hectare, or 14% lower yield (95% CI 4–29%) than what we estimate in the research-managed trials with traditional seeds and no fertilizer (see Online Appendix Table A.2). Average yearly yield varies over time, although not strikingly so at the national level, where average yield varied between 1.3 and 1.6 tons per hectare over the period 2009–2013. Average maize yield for the sample of smallholder farmers surveyed here (also in 2013 and using traditional techniques) was 1.4 metric ton per hectare, or 22% lower yield than in the research-managed trials.

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fertilizer samples bought in local markets, while the rate of return for authentic technologies is approximately 50%.

We estimate rates of return based on data for one season. The broad spatial variation in the data (we use data from five agricultural stations spanning three regions) likely relaxes some concerns about the generalizability of the estimates. However, because small-scale agriculture in Africa largely relies on rain-fed irrigation, yield is a function of weather realizations, which vary over time (see Rosenzweig and Udry 2016). Differences in yield are also likely to map into differences in net income (value of output minus cost of inputs and hired labor), and relatively small changes in yield can result in relatively large differences in net income returns.[13] Here, we focus on rates of return, defined as the difference between net income and revenues from traditional farming, expressed as a share of the total costs of the investment. To the extent that yields and revenues from farming using both traditional and modern technologies vary over time as a function of weather realizations, the difference between them will net out some time-series variation due to weather shocks. More important, we focus on the difference between rates of return using technologies from local markets versus authentic technologies, both of which are functions of weather realizations. In fact, if we approximate the relationship between the state of nature and yields (or revenue) with the linear function $\varphi p^m \hat{y}(n_j, s_k)$, where φ represents the state of nature, Online Appendix Figure A.2 also illustrates the impact of different weather realizations. An adverse weather shock resulting in revenues from farming, independent of technology choice, falling by say 20%, lowers the mean rate of return for technologies in the market from 7% to –15% and lowers the mean rate of return for authentic technologies from 84% to 48%. A positive weather shock leading to an increase in revenue by 20% raises the rate from 7% to 28% and 84% to 120% for technologies in the market and authentic technologies, respectively. In both cases there are large differences in rates of return from using technologies available in local markets versus authentic technologies.

Finally, it is possible that the labor costs when adopting authentic technologies at harvest are higher than the labor costs when using substandard inputs, simply because labor costs are a

13. Note that the state of nature (weather realization) may also affect prices (for outputs and inputs).

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function of yields. Assuming for small-scale farming that approximately a third of all labor costs are incurred at harvest, consistent with the findings reported in, for example, Suri (2011), and assuming further that our estimate of l^{fs} captures the average total complementary labor cost of adoption of inputs from the market, then for a farmer using inputs with average market quality $(\bar{n}, s_2)$, labor cost at harvest, per metric ton per hectare, is $\frac{l^{fs}}{3\hat{y}(\bar{n},s_2)}$. If costs are linear in yield, the (labor) costs incurred at harvest when using authentic inputs are then simply $\frac{\hat{y}(46,s_3)\times l^{fs}}{3\hat{y}(\bar{n},s_2)}$. This increase in costs, however, has only a modest impact on the rate of return. Compared with the baseline scenario reported in Table V, Panel A, the average rate of return of adoption with authentic inputs goes down from 84% to 77% and all fertilizer samples continue to yield a rate of return over 60%.

VI. Farmers' Expectations

Can poor quality of fertilizer and seeds and low rates of return help explain why farmers do not adopt modern inputs? For that to be a plausible explanation, it ought to be the case that (i) farmers expect that technologies available in the market are of poor quality, and (ii) that farmers expect that there is a positive relationship between quality of inputs and yields. We turn to these issues next.

A farmer (household) survey was administered to a sample of farmers at the end of the second season of 2013. For each trading center visited as part of the 2014 fertilizer study, 10 farmers within a 5-km radius from the trading center and 10 farmers in 5–10-km distance from the trading center were surveyed, using a two-stage sampling strategy (see Online Appendix for details). The objective of the survey was to collect detailed information from small-scale maize farmers on their agricultural practices and their expectations about the quality of and economic return to fertilizers. In total, information was collected from 312 smallholder farmers.

The subjective expectations module was designed to elicit a farmer's probability distribution over yield generated by growing maize on their land either (i) without using fertilizer, (ii) by applying the recommended amount of urea using fertilizer bought from the nearest shop, or (iii) by applying the recommended amount of urea using fertilizer of the best official quality. Specifically, farmers were first asked to give an estimate of the range of the

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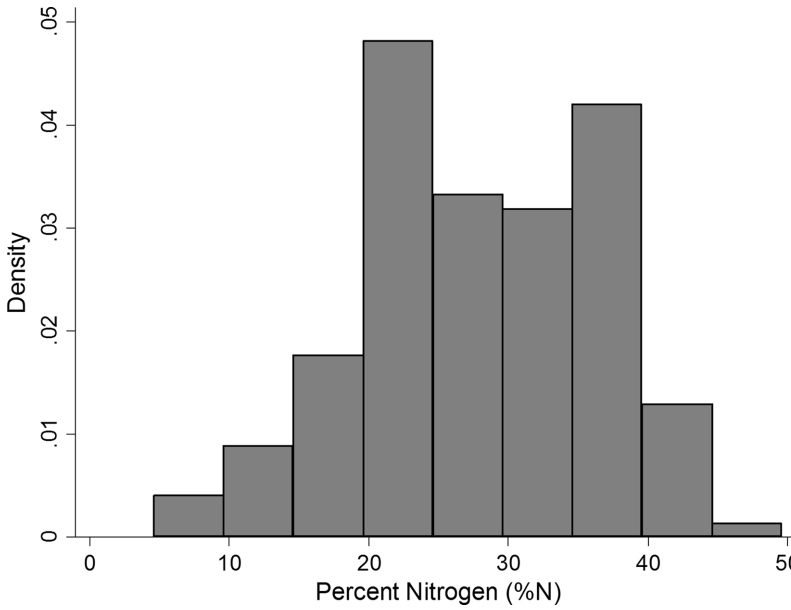

FIGURE V

Farmer Beliefs: Percent Nitrogen (%N) in Nearest Shop

The bars present the percentage of farmers' beliefs about nitrogen content (percent nitrogen; %N). Data from the household survey, 295 farmers.

distribution. The enumerator then calculated three evenly spaced mass points between the minimum and the maximum stated by the farmer. For each elicitation, farmers were given 10 beans and instructed to place the beans on a plate describing the chance that the event in question would be lower or equal than this number. We also collected data on farmers' beliefs about the nitrogen content of fertilizers in the nearest local shop by asking the respondent to assess the quality of fertilizer on a scale of 1 to 10, where 0 means there is no nitrogen, 5 means that half of the official nitrogen is there, and 10 is the best possible quality.[14]

Figure V shows the histogram of farmers' beliefs about the nitrogen content of fertilizer in their nearest shop. On average,

14. See Delavande, Giné, and McKenzie (2011) for a review and analysis of subjective expectations data from developing countries. Despite our attempt to minimize measurement errors, these data should be interpreted with caution because we do not know whether the respondents fully understood the key concepts.

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TABLE VI
FARMER BELIEFS: PERCENT NITROGEN (%N) IN NEAREST SHOP

	Mean	Std.	Min	Max	Obs.
%N	28.4	8.0	4.6	46	295

Notes. The values provide summary statistics of the expected nitrogen content in the nearest retail shop from the farmer survey. See text and Online Appendix A2 for details.

farmers expect fertilizer bought in the marketplace to contain 38% less nutrient, equivalent to a nitrogen shortfall of 17.6 percentage points (Table VI). That is, expectations are on average in line with the results we obtained from the fertilizer samples tested (see Table I). There is substantial variation, however, even among households close to the same trading center. Taken together, the results suggest that although farmers as a group predict average quality relatively well, individual farmers' ability to infer quality appears to be more limited.

In Table II, column (4), we report a linear regression of a farmer's expectation of yields on her expectation of nitrogen content (%N) in fertilizers bought in the nearest shop, where the latter has been rescaled to range from 0% to 46%. As is evident, there is a strong correlation between the expected quality of the fertilizer and expected yield. Moreover, the estimated return to nitrogen based on the farmer's expectations is similar to the estimates from the experimental plots.

Figure VI puts the two findings together—farmers expect fertilizers in the market to be of low quality and lower quality is expected to result in lower yield—by plotting the CDF of farmers' expectations of yields conditional on technology choice and source of the technology. The CDF of expected yield using authentic fertilizers is strongly shifted to the right of the CDF of farmers' expectations of yields using market quality fertilizer, which in turn lies to the right of the CDF without fertilizers. A Kolmogorov-Smirnov test rejects the equality of the three distributions at the 1% level.

VII. RATIONALIZING THE EQUILIBRIUM: LEARNING ABOUT QUALITY

We have shown that poor-quality inputs are the norm in the retail markets we surveyed—spanning two of the main maize-growing regions of Uganda—and that only a small share of the fertilizers we observe in the market appear profitable. In this section we start to rationalize the market equilibrium by zeroing

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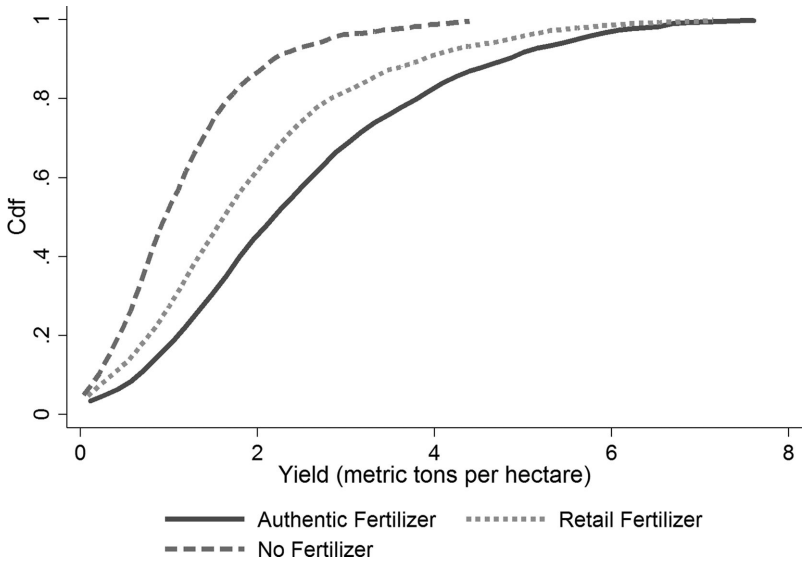

FIGURE VI

Farmer Expectations: Cumulative Distribution of Maize Yield

The solid line represents the cumulative distribution of expected yields in metric tons per hectare when using authentic fertilizer. The dotted line represents the cumulative distribution of expected yields when using retail fertilizer. The dashed line represents the cumulative distribution of expected yields when not using fertilizer. Data from the household survey.

in on one key determinant of the equilibrium: farmers' ability to learn about quality.

Fertilizers and hybrid seeds are experience goods; that is, farmers typically observe neither the quality of the technology nor the additional output their adoption would yield before purchasing them. In largely unregulated and unmonitored markets for such goods, a retailer's incentive to provide high-quality goods hinges crucially on the buyers' ability to learn about quality after using it (Shapiro 1982; Mailath and Samuelson 2001).

In assessing the quality of the inputs after use—based on yields after adoption—farmers, especially smallholder farmers, face a difficult inference problem. Even holding farming practice and quality of the inputs constant, yields vary due to a number of factors that are mostly unobservable to the farmer, including the fertility status of the soils and the inherent variability of seeds.

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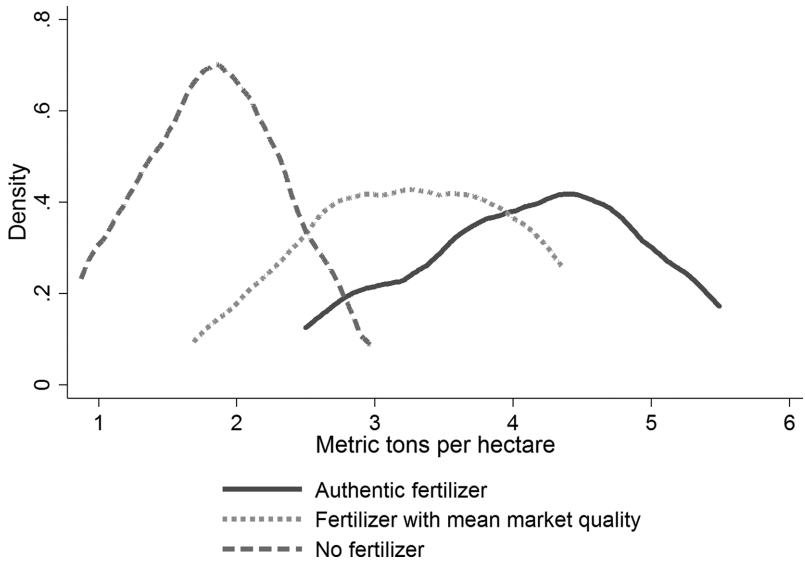

FIGURE VII

Densities of Yield for Different Input Qualities

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

Thus, a farmer must disentangle the quality of inputs from a noisy yield signal.

Figure VII illustrates the inference problem by plotting the density of yields for three quality combinations—authentic inputs, inputs with mean market quality, and inputs with the lowest quality—using data from the researcher-managed agricultural trials. Even holding quality and agricultural practice constant, yield varies substantially across plots.

The results presented so far provide indirect evidence of the learning environment. Low quality is the norm in the market; however, the nutrient content in fertilizers is not zero and the market has not collapsed, suggesting that farmers do learn about quality to some extent. At the same time, the variation in quality we observe appears uncorrelated with price, suggesting that

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farmers' ability to infer quality is far from perfect, otherwise one would expect prices to adjust.

We now present a simple learning model, which we calibrate using data from the researcher-managed agricultural trials, to calculate a Bayesian farmer's confidence that the fertilizer she is experimenting with is profitable and the resulting willingness to pay for it. We use the model to answer two questions. (i) What range of quality levels would one expect to find in the market given a farmer's (limited) ability to learn about the quality of inputs? In other words, can learning in a noisy environment explain why the market looks like it does? (ii) Would a seller selling authentic fertilizer be able to build up a reputation for doing so both under the status quo and when additional constraints are lifted?

VII.A. A Model of Learning about Quality

Consider a farmer who wants to adopt fertilizer and starts experimenting with it on a small plot.[15] The farmer knows that fertilizer of sufficiently high quality, say, with a rate of dilution $\theta < \theta^*$, where θ^* is the threshold level, is profitable. However, the farmer cannot directly observe the quality of the fertilizer in the market; that is, the dilution level $\theta \in [0,1]$ is unknown. The farmer must therefore infer quality based on the yields on her plot.

The farmer knows that the systematic relationship between yield (y) and the quality of inputs is given by

$$y = g(\theta). \tag{2}$$

Furthermore, the farmer has some prior belief about the distribution of fertilizer quality on the market $\Pi(\theta)$ (with density $\pi(\theta)$).[16]

15. The assumption that the farmer starts experimenting on a small plot can be motivated in different ways. For example, credit or cash constraints, which have been shown to be important in recent experimental studies on adoption (Duflo, Kremer, and Robinson 2011; Karlan et al. 2014), may force farmers to start small. More generally, low profitability and high uncertainty could also constrain the scale of experimentation.

16. Our model is related to those in Foster and Rosenzweig (1995) and Conley and Udry (2010), where farmers learn about the optimal level of fertilizers to be applied, which in our setup corresponds to learning about the $g()$ function. We consider learning about the quality of fertilizer rather than the optimal amount to apply. Indeed, to home in on the dimension of learning relevant to our data, we assume that farmers know the optimal quantities and how these (on average) translate into yields, $g(\theta)$, but they do not observe the quality of the technology.

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In period (or on plot) $t = 1$, a farmer experiments with fertilizer with an unobserved dilution level $\theta_t = \hat{\theta}_t$ randomly drawn from a distribution $F(\theta)$, and receives a private signal ω_t about y, after each experimentation (harvest), given by

$$\omega_t = g(\hat{\theta}_t) + \varepsilon_t, \tag{3}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$ is a noise term that is unobserved but whose distribution is known to the farmer. Note that ε_t is assumed not to be a function of the unknown input quality.

Observing a signal ω_1, a Bayesian farmer will update his belief; that is, the density of the distribution over θ, at any point θ. By Bayes' rule the updated posterior density is

$$\pi(\theta|\omega_1) = \frac{f(\omega_1|\theta)\,\pi(\theta)}{\int_0^1 f(\omega_1|\theta)\,\pi(\theta)d\theta}, \tag{4}$$

where $f(\cdot|\theta)$ is the distribution of the signal conditional on the farmer's belief about quality. Iterating on this expression, we can write the density of dilution level θ after experimenting for t rounds (or on t plots) as

$$\pi(\theta|\omega_1, \ldots, \omega_t) = \frac{\prod_i f(\omega_i|\theta)\,\pi(\theta)}{\int_0^1 \prod_i f(\omega_i|\theta)\,\pi(\theta)d\theta}, \tag{5}$$

where $\pi(\theta)$ is the initial prior density.

To examine the speed and ease of learning about quality, we consider a farmer's confidence in determining whether the fertilizer she is experimenting with is profitable in the sense that it corresponds to a dilution level below or above the cut-off θ^*. The posterior odds ratio; that is, the probability that fertilizer is profitable given the observed signal relative to the probability that fertilizer is not profitable given the signal is

$$\frac{P(\hat{\theta} \leqslant \theta^*|\omega)}{P(\hat{\theta} > \theta^*|\omega)} = \frac{\int_0^{\theta^*} \pi(\theta)d\theta}{\int_{\theta^*}^1 \pi(\theta)d\theta} \times \frac{\int f(\omega|\theta, \theta \leqslant \theta^*)\,\pi(\theta|\theta \leqslant \theta^*)d\theta}{\int f(\omega|\theta, \theta > \theta^*)\,\pi(\theta|\theta > \theta^*)d\theta}, \tag{6}$$

In the case of learning about the dilution of a single-nutrient fertilizer, we could in principle rewrite the model along the lines of Foster and Rosenzweig (1995) and Conley and Udry (2010) and let farmers experiment with identifying the right amount of fertilizer to apply to compensate for the unknown dilution level in the market.

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which is just the prior odds ratio times the ratio of marginal likelihoods, or the Bayes factor (see Greenberg 2013).

We consider two variants of the learning environment. In the first version, we assume that farmers experiment with constant fertilizer quality $\hat{\theta}$, drawn from the market density. In the second version we instead let farmers draw a new quality level $\hat{\theta}_t$ from the market density in each period.[17]

The posterior odds ratio provides an illustrative way to examine the learning environment without having to specify the relationship between quality, expected utility, and demand. With more structure, however, we can also estimate the hypothetical farmer's willingness to pay (*WTP*) for fertilizers as a function of the dilution rate $\hat{\theta}$. To do so, we compare the expected utility of adopting fertilizer, where the expectation is taken over the farmer's posterior density of fertilizer dilution given the harvests she has observed during experimentation, to the certain return (in utility terms) of farming using traditional methods.[18] Specifically, let the systematic relationship between yield and quality of inputs be given by equation (2). We assume that to invest in modern inputs, the farmer can borrow at a rate r (or that is her outside return on the funds used for investment). We further assume that utility is separable in consumption and leisure. Given the results in Section V, we assume that the additional labor for fertilizer use is hired labor, denoted l^h. The willingness to pay for fertilizer of

17. A smaller follow-up study was implemented during the first season of 2016 (see Online Appendix). In the follow-up study, we repeatedly sampled (once every month) and tested DAP from nine stores in three regions. Defining dilution of a DAP fertilizer sample as the weighted average of the dilution of the two main nutrients (nitrogen and phosphorus), we find an average dilution rate of 26%. Decomposing the variance, the between-store standard deviation is about five times larger than the within-store standard deviation, suggesting that the model variant in which farmers experiment with constant fertilizer quality is more appropriate.

18. The assumption that the yield from farming with traditional methods is certain is simplifying and could be relaxed without changing the qualitative findings. However, because farmers have typically farmed with traditional methods over a long period and on a larger scale, presumably the uncertainty is significantly smaller than when experimenting with modern inputs.

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quality $\hat{\theta}$, $WTP(\hat{\theta})$, is then implicitly defined by equation (7),

$$(7)\quad \int_0^1 \pi(\theta|\omega_1, \ldots \omega_t) u(p^m g(\theta) - (1+r)(l^h + WTP(\hat{\theta})))d\theta - \psi(l^f) \geqslant u(p^m g(1)) - \psi(l^f),$$

where l^f is the amount of family labor and $\psi(l^f)$ the value of leisure. Note here that, consistent with the assumption on the relationship between yield and the quality of inputs (equation (2)), we assume that yield when adopting at scale (here normalized to one hectare) is given by $g(\theta)$. Thus, to focus on how uncertainty about quality influences willingness to pay, we abstract from the uncertainty related to the realization of yields for a given dilution level when going to scale. However, as a comparison, we also report estimates of the *WTP* that incorporate such additional uncertainty (see Section VII.C).

VII.B. Calibrating the Model

To use the model to assess farmers' confidence in inferring quality and their willingness to pay we need to solve equations (6)–(7).[19] To do so we need to specify the systematic relationship between yield (y) and quality of inputs (θ), that is, equation (2). We also need to estimate the variance of the unobserved noise term σ_ε^2 in the signal equation (3), determine the profitability threshold θ^*, and make an assumption about the farmer's prior belief about the distribution of fertilizer on the market, $\Pi(\theta)$. Finally, to estimate the willingness to pay we further need to specify the price of maize and the cost of adoption and parameterize farmers' preferences.

Consistent with the findings reported in Table II and illustrated in Figure IV, we assume that the yield function, $y = g(\theta)$, can be approximated by a linear function. We then use the experimental yield data to estimate the parameters of this function. Specifically, using data from the research managed trials, we estimate (by OLS)

$$(8)\qquad y_j = \alpha + \beta_\theta \theta_j + e_j,$$

where y denotes total yield per hectare, $\theta = \frac{(46 - \%N)}{46}$, and subscript j refers to a plot. To consider learning about fertilizer quality, we

19. The integrals in equation (6) are evaluated numerically using Gauss-Chebyshev quadrature.

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consider one type of seed (farmer seeds), so we drop subscript k. As inputs were randomly assigned across plots, β_θ captures the causal effect of inputs on yields.

Letting a and b_θ denote the estimated parameters in equation (8), our empirical counterpart of equation (3) is then given by

$$y = g(\theta) = a + b_\theta \theta. \tag{9}$$

We also use experimental yield data to estimate the variance of the unobserved noise term. Specifically, we use the distribution of the residual from regression (8) as an estimate of the distribution of the noise in the signal equation; that is we set $\sigma_\varepsilon^2 = \sigma_e^2$, where σ_e^2 is the variance of the residual in regression (8). In essence we assume that the density of yields for a given quality, derived using data from a large set of plots where identical inputs have been employed, provides a good proxy for the uncertainty about quality that farmers face when experimenting on their own plots. We then decompose this variation into two components: the variation accounted for by the inputs, $g(\theta)$, and the unexplained variation, that is, the noise term in equation (3).

Two remarks about this approach are in order. First, we assume that the noise term in the signal equation (3) is homoskedastic, that is, it is not a function of the level of dilution. A White (1980) test for heteroskedasticity also confirms that this assumption is consistent with the data.[20] Second, an advantage of using data from the agricultural trials is that the variation in yields across plots, and especially the estimated noise in the data, for a given, randomly assigned technology bundle, are not driven by variation in farmer-specific factors or inflated by measurement error problems. Nevertheless, it is possible that our estimate of the distribution of the noise in the signal equation, and thus the learning environment, may not capture the learning environment faced by many smallholder farmers very well. Our estimate may understate the learning problem if farmers do not manage their plots consistently. We would also underestimate the severity of the learning problem if experimentation primarily takes place over time, and farmers cannot perfectly filter out ex post differences in weather shocks and if the signal-to-noise ratio is a function of

20. The standard deviation of the residual in regression (8), σ_e, is 0.77. The test statistic for the null hypothesis of homoskedasticity is $\chi^2 = 4.23$, with p-value $= .13$.

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these shocks.[21] Our estimate may overstate the learning problem if, for example, farmers experiment on larger plots than in our agricultural trials and the idiosyncratic variations we pick up in the agricultural trials are decreasing in plot size, which seems likely.

To get a sense of how well our cross-sectional estimate captures the variance in returns among farmers both over time and space, we exploit data from the Uganda LSMS-ISA. The Uganda National Panel Surveys contain four waves of household survey data from which plot-specific measures of yield can be derived for two seasons each in 2009, 2010, 2011, and 2013. As reported in Section II, relatively few farmers use fertilizers and hybrid seeds, so we focus on the subsample of farmers using traditional farming methods. We then estimate a simple farmer fixed effects regression (see Online Appendix), controlling only for plot size, and estimate the standard deviation (σ_{LSMS}) of the residual from the regression and the relative standard deviation (the standard deviation of the residual divided by the mean of the dependent variable). The results are reported in Online Appendix Table A.2. Average maize yields vary between 1.3 and 1.6 metric tons per hectare, and the relative standard deviation varies between 0.26 and 0.55, over the four waves (year). Pooling data for all four years gives an average maize yield of 1.4 metric tons per hectare and a relative standard deviation of 0.70. Using experimental data from the subset of plots with traditional inputs (no fertilizer and traditional seeds), we estimate an average maize yield of 1.8 and a relative standard deviation of 0.29. Thus although the variance in yield returns is larger in the LSMS data relative to the experimental data, especially in the pooled data spanning five years, the difference is relative modest, suggesting that the learning environment we study here is fairly representative of the learning environment facing Ugandan farmers more generally.

Finally, we assume a 25% rate of return for profitability, which is close to the official interest rate, and we use equation (1) to back

21. In a rain-fed irrigation system as in Uganda, the timing and level of rains matter for yields. The severity of the learning problem, however, depends on the signal-to-noise ratio (in the model specifically the ratio $\frac{b_\theta}{\sigma_e}$). This implies, for example, that if we assume that yield is a linear function $\varphi\hat{y}(n_j, s_k)$ of the state of nature φ, then variations in φ, while affecting both b_θ and σ_e, will not affect the ratio $\frac{b_\theta}{\sigma_e}$.

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out the implied profitability threshold θ^*, which from Table V is a dilution rate of 17%, equivalent to 38%N.

To estimate the *WTP*, we use the estimates of price and costs as discussed in Section V and assume that farmers have preferences that are characterized by constant relative risk aversion.[22]

VII.C. Results

We now use the learning framework derived above to start rationalizing the equilibrium we observe. To do so, we investigate, within the model, Bayesian farmers' ability to infer quality and willingness to pay conditional on the level of dilution, when the farmers initially only know the possible range of fertilizer dilution in the market; that is, $\hat{\theta} \in [0,1]$. The first experiment thus provides information about the likely quality range that would emerge in the market if farmers initially have little information. We focus on three questions: (i) Is the learning environment such that high levels of dilution will be found out very quickly and farmers would therefore not be willing to pay for such fertilizers—consistent with the absence of fully diluted fertilizers in our sample? (ii) Would risk-averse Bayesian farmers be willing to buy samples with intermediate dilution levels—consistent with the range of dilution levels available in the market—and is the share of farmers willing to buy fertilizer similar to what is observed in the household data? (iii) Finally, is the range of quality supplied in the market consistent with seller profit maximization given farmers' ability to learn and willingness to buy fertilizer of a given quality?

We then turn attention to a more hypothetical question: do sellers selling authentic fertilizer have pecuniary incentives to enter the market given the surveyed farmers' beliefs about fertilizer quality, under the status quo and when additional constraints are lifted?

1. Why Does the Market for Fertilizer Look Like It Does? As a first step toward understanding why we observe the distribution of fertilizer quality that we do, we derive a relationship between the dilution level of fertilizer and a Bayesian farmer's ability to learn about fertilizer profitability from experimentation. To trace this relationship, we consider all possible dilution levels, that is,

22. For the main results, we assume that the coefficient of risk aversion is 2. We have found the results to be broadly the same for intermediate levels of risk aversion.

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$\hat{\theta} \in [0,1]$, and let the farmer experiment $1 \ldots T$ times for each dilution level. We assume that the farmer knows the range of fertilizer dilution but has no other information. Her prior is thus best described by a uniform distribution over [0,1]. We evaluate her confidence in inferring quality when she receives an unbiased private signal ω_t about fertilizer quality after each period of experimentation (that is, the randomly drawn noise term ε_t takes the value 0).

In Figure VIII, Panel A, we plot the Bayesian farmer's log10 odds ratio in favor of fertilizer being unprofitable, $\log10(\frac{P(\hat{\theta}>\theta^*)}{P(\hat{\theta}\leqslant\theta^*)})$, for each possible dilution level after 1, 5, and 10 rounds of experimentation.[23] We also categorize the learning environment, conditional on $\hat{\theta}$, into three regions based on how fast the Bayesian farmer learns over time. To that end, we calculate the marginal likelihood after five periods; specifically, we filter out the prior by taking the difference between the log10 posterior and prior odds ratio. Following standard notation, we label an absolute change in the log10 odds ratio of 1 or greater as regions characterized by strong learning; an absolute change in the log10 odds ratio smaller than 1 but greater than 0.5 as a region characterized by moderate learning, and an absolute change in the log10 odds ratio smaller than 0.5 as characterized by weak learning.[24]

There are large variations in the speed of learning across the range of dilution rates. For high levels of dilution ($\hat{\theta} \geqslant 0.5$), learning is fast. As a result, the farmer quickly concludes that fertilizer is unprofitable, with strong evidence against profitability accumulating after one (three) [five] periods if the rate of dilution is above 55% (42%) [37%].

For intermediate dilution rates, however, learning is either moderately fast ($0.40 < \hat{\theta} < 0.50$) or slow ($0.18 < \hat{\theta} \leqslant 0.40$), which implies that it takes more than 10 rounds of experimentation

23. We present the log10 odds ratio because of its symmetry properties: a log10 odds ratio of 1 implies that the farmer thinks it is 10 times more likely that fertilizer is not profitable (than that it is) and a log10 odds ratio of –1 implies that she thinks it 10 times more likely that fertilizer is profitable (than that it is not).

24. Jeffreys (1961) and Kass and Raftery (1995) suggest interpreting the strength of the evidence in favor of model M_1 as "decisive" if the posterior log odds ratio $\geqslant 2$ in favor of model M_1 relative M_2, and as "strong" if the posterior log10 odds ratio $\geqslant 1$ in favor of the alternative. If the posterior log10 odds ratio $\leqslant 0.5$ but greater than 0, Jeffreys (1961) and Kass and Raftery (1995) label the evidence in favor of model M_1 as "weak" or "inconclusive." If $0.5 <$ posterior log10 odds ratio < 1, they suggest interpreting the evidence as "positive" or "moderate."

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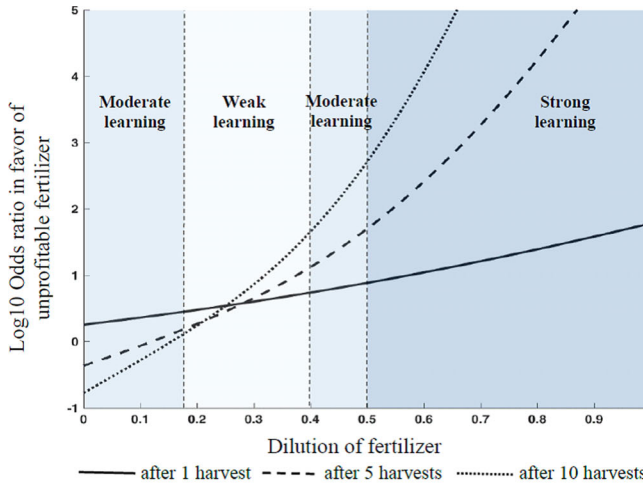
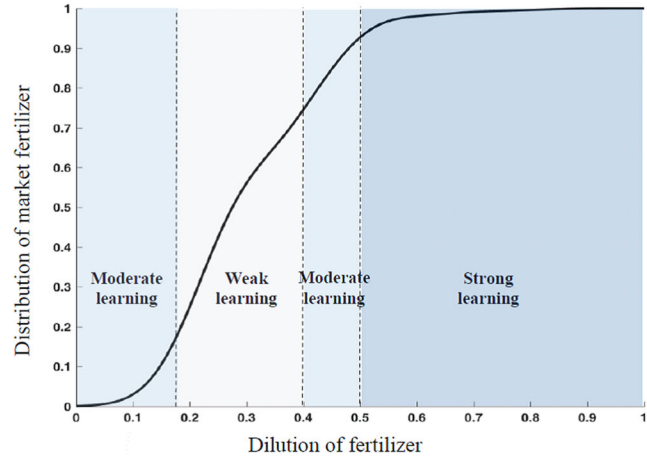


Panel A: Evidence in favor of fertilizer being profitable or not



Panel B: Learning about fertilizer quality and distribution of market fertilizers

FIGURE VIII

Learning about Fertilizer Euality: Evidence in Favor of Fertilizer Being Profitable or Not

Panel A: Log10 odds ratios in favor of fertilizers being profitable relative to being unprofitable after 1 (solid line), 5 (dashed line), and 10 (dotted line) rounds of experimentation. Panel B: Distribution function of fertilizer quality in the market (solid line). Strong learning if the absolute change in the log10 odds ratio (marginal likelihood) is greater or equal to 1; moderate learning if the absolute change in the log10 odds ratio is smaller than 1 but greater than or equal to 0.5; and weak learning if the absolute change in the log10 odds ratio is smaller than 0.5.

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to amass strong evidence that fertilizer of average quality is unprofitable.[25] As quality increases and fertilizer becomes profitable, learning speeds up again, but this is not sufficient to convince the farmer that fertilizer is profitable given the initial beliefs. In fact, it takes three or more rounds of experimentation to accumulate any evidence in favor of profitability for most fertilizers in the authentic to almost authentic region (a shortfall of %N of less than 10%), and even after 10 periods, the evidence remains weak and inconclusive for most fertilizers in this range.[26]

To show that farmers' ability to learn about quality plausibly constrains the amount of dilution in the market, we combine the relationship between dilution and learning with the distribution of quality in the fertilizer samples purchased by the covert shoppers. In particular, in Figure VIII, Panel B, we plot the distribution function of fertilizer quality in the market samples and overlay this with the learning regions from Panel A. Consistent with the finding that farmers are able to deduce that fertilizer is not profitable when the dilution of nutrients in fertilizer is high, we observe few samples with very low nitrogen content: less than 5% of samples lie in the range where learning is fast ($\hat{\theta} > 50\%$). Conversely, approximately 60% of the samples are located in the range where learning is slow and uncertainty about profitability is large.

Beause farmers have great difficulty in determining the profitability of most of the fertilizers in the market sample, it is natural to ask to what extent this affects demand. To answer this question, we now consider at each dilution rate, $\hat{\theta} \in [0,1]$, $N = 1{,}000$ initially uninformed farmers. The farmers experiment with fertilizer of quality $\hat{\theta}$ for T rounds and receive a signal with random

25. Learning after one period in our model is slower than after the one harvest intervention in Hanna, Mullainathan, and Schwartzstein (2014). In Hanna, Mullainathan, and Schwartzstein (2014) farmers are presented with information on optimal seaweed pod size based on a larger number of experiments, equivalent to many more rounds or larger scale of fertilizer experimentation in our model, whereas in our model farmers learn from experiments one plot/period at a time.

26. If we do not restrict attention to unbiased signals, so each farmer receives a unique sequence of signals, farmers will initially draw different conclusions about the quality on the market for a given quality. Random signals will also result in farmers switching from being relatively confident that quality is high to quality being low. This result, in turn, may help explain why smallholder farmers, as documented in several studies (e.g., Duflo, Kremer, and Robinson 2006; Dercon and Christiaensen 2011; Suri 2011), switch into and out of hybrid seed and fertilizer use over time.

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noise about the fertilizer's quality after each period. From this, we calculate each farmer's posterior distribution, their net expected utility and willingness to pay (see equation (7)) for fertilizer of dilution rate $\hat{\theta}$ after $t = 1, \ldots, T$.

In Figure IX, Panel A, we plot the average as well as the 95th percentile of the willingness to pay, normalized by dividing by the cost of adoption at average market prices, across the N farmers at each dilution rate after five rounds of experimentation. For fertilizers with dilution rates above 50%, effectively no farmer has a *WTP* above average market prices; that is, farmers' ability to detect high dilution implies that farmers would not be willing to buy them at current market prices.

Turning to the moderately diluted fertilizers (<40% dilution), we see that lack of confidence about profitability also constrains willingness to pay in this range: the average normalized *WTP* is below the (average) market price for almost the full range of quality after five periods and rises just above 1 for fertilizers with dilution levels of 4% or below.

For fully authentic quality, where the *WTP* would be 55% above average market price if quality was certain, it takes five periods before the average willingness to pay rises above the average market price.

That the average willingness to pay is below average market price for almost all dilution levels does not imply zero demand, however. Learning implies that farmers respond to both signal and noise, so there will be farmers who end up with a *WTP* equal to or above the (average) market price at early stages of experimentation, even though for the most part fertilizer quality is too low to be profitable. In fact, the 95th percentile of the *WTP* is above the (average) market price after five periods of experimentation for dilution levels up to the mean market level (Figure IX, Panel A). Hence there is a group of farmers with willingness to pay above market price, which consists of two types: those who experiment with fertilizer that is not profitable but who have observed higher than average yields (given the level of dilution) in a small number of experiments, and those who experiment with fertilizer that is profitable.

Over time, as farmers become more confident about the quality of the fertilizer they are experimenting with, the spread of the willingness to pay is reduced while its average increases. Together these effects imply that the share of farmers willing to buy at market price increases for profitable fertilizers, whereas it is

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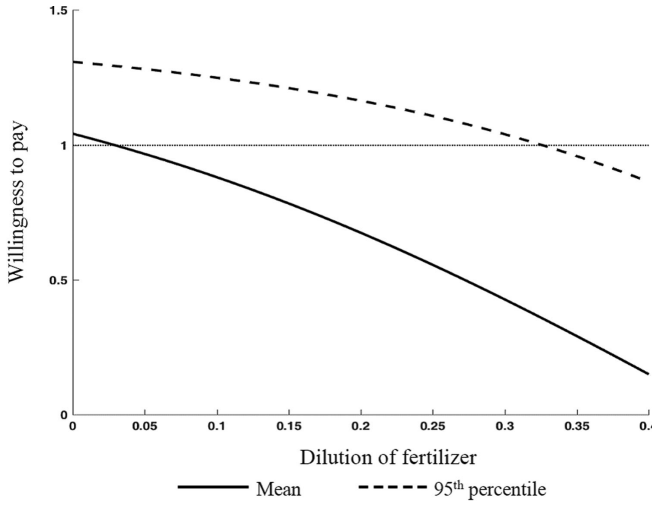
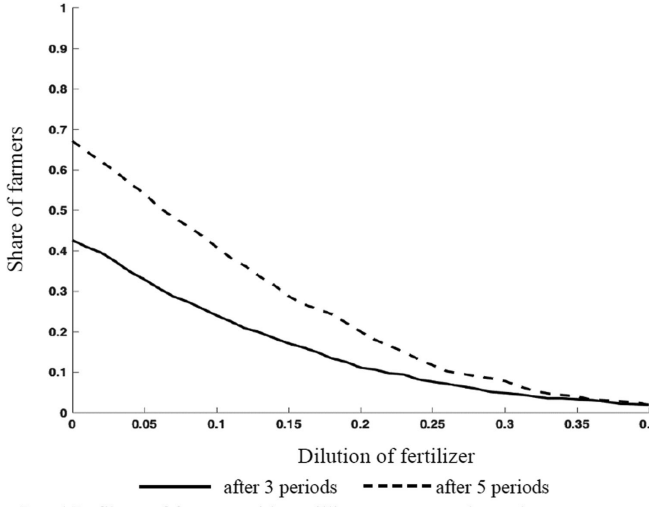


Panel A: Willingness to pay (*WTP*) after 5 periods



Panel B: Share of farmers with a willingness to pay above the average market price

FIGURE IX

Willingness to Pay (*WTP*)

Panel A: Average (solid line) and the 95th percentile (dashed line) of the normalized willingness to pay conditional on the level of dilution of fertilizers after five periods of experimentation. Panel B: Share of farmers with a willingness to pay above the (average) market price ($WTP > 1$) after three (solid line) and five (dashed line) periods.

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TABLE VII

WILLINGNESS TO PAY (WTP) AND ADOPTION RATES

Panel A: Model estimates

	$WTP > 1$			$(WTP \mid \hat{\theta} \leqslant \theta^*) > 1$		
Periods of experimentation	3	5	15	3	5	15
Share of farmers (constant quality draws)	7.7%	12.5%	17.9%	2.7%	4.5%	7.8%
Share of farmers (time variant quality draws)	6.3%	6.4%	5%	—	—	—

Panel B: Household survey data

	Used urea in last seasons		Conditional on urea use in season 1, used urea in season 2
	Season 1	Season 2	
Share of farmers	12.6%	10.2%	59.5%
Number of farmers	294	295	294

Notes. Panel A reports estimates from the Bayesian model (see text for details). The first three columns ($WTP > 1$) depict the share of farmers (after 3, 5, and 15 periods) with a normalized willingness to pay above the (average) market price and the three last columns ($WTP|\hat{\theta} \leqslant \theta^*) > 1$ depict the share of farmers (after 3, 5, and 15 periods) with a normalized willingness to pay above the (average) market price conditional on drawing a profitable fertilizer sample ($\hat{\theta} \leqslant \theta^*$). The first row reports the results when farmers experiment with constant fertilizer quality $\hat{\theta}$ drawn randomly from the market distribution. The second row reports the results when farmers draw a new quality level $\hat{\theta}_t$ from the market density in each period. Panel B reports summary statistics from the household survey data. The first two columns report the share of farmers, by season (first and second season of 2013), reporting to have used urea on at least one plot. The last column reports the share of farmers that continued to use urea on at least one plot in season 2, conditional on using urea in season 1.

more stagnant for unprofitable but not too highly diluted fertilizers ($0.3 < \theta < 0.4$) (see Figure IX, Panel B).

Combining this information with the distribution of dilution in the fertilizers we sampled as part of the covert shopper approach (see Figure I), we can infer the likely demand sellers would face if prices are fixed. Assuming that farmers experiment with constant fertilizer quality $\hat{\theta}$ drawn randomly from the market distribution, we find that 12.5% of farmers end up with a willingness to pay equal to or higher than the current market price after five rounds of experimentation (see Table VII, Panel A). Of these, just over a third would buy from sellers selling profitable fertilizer and just under two thirds would be overly optimistic and buy from sellers with moderate dilution rates. If instead, farmers drew a new quality level $\hat{\theta}_t$ from the market density in each period, the share of farmers with a willingness to pay at least average market price is halved after five periods. This is the case because the additional uncertainty that comes with the variation in $\hat{\theta}$ complicates the inference problem even more.

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As time passes, the share of farmers with a willingness to pay greater than the market price increases, but the composition of demand remains fairly constant, at least over the medium run.

Of course, with Bayesian learning, the proportion of overly optimistic farmers willing to buy unprofitable fertilizer would eventually shrink to 0. But this happens quite slowly; even after 20 periods of experimentation, when around one in five farmers are willing to buy at market price, the share of those buying unprofitable fertilizer is still roughly 50%. Put another way, in our model, a seller selling unprofitable but not too diluted fertilizers, can still expect to capture a (small) part of the market for a relatively long period of time.

Table VII, Panel B, reports the closest empirical counterpart, using data from the household survey, to the estimates in Panel A. Urea use varied between 10.2% and 12.6% over the last two seasons—numbers that are similar to the 13% (17%) of farmers with a *WTP* above the (average) market price in the model after 5 (10) periods. Moreover, conditional on using urea in the first of the two seasons for which we have data, 59.5% continue to use it the following period, which again is broadly consistent with the model's prediction that about half of the farmers with a *WTP* above the (average) market price buy from sellers selling profitable fertilizer, assuming that farmers that manage to buy fertilizers of sufficiently high quality would continue to do so.

Finally, we ask whether the range of quality observed in the market could be consistent with sellers who maximize profits taking farmers' willingness to pay for fertilizer as given. If we assume that sellers are local monopolists and compete on quality, that is, the price is fixed or taken as given, then the share of farmers with willingness to pay above the (average) market price in Figure IX, Panel B could be interpreted as the seller's demand as a function of dilution. If in addition, the cost of supplying quality is increasing and convex, it is straightforward to show that the profit-maximizing dilution level is increasing in the slope of the demand curve.[27] That is, the steeper the demand curve, the lower dilution. As illustrated in Panel B, as farmers become more con-

27. Denote demand as a function of dilution by $d(\theta)$ and cost by $c(\theta)$. Profit maximization implies that $pd_\theta(\theta) = c_\theta(\theta)$, with a maximum implying $pd_{\theta\theta} < c_{\theta\theta}$. Differentiating the first-order condition and rearranging gives $\frac{\partial \theta}{\partial d_\theta(\theta)} = \frac{-p}{pd_{\theta\theta} - c_{\theta\theta}}$, which is greater than 0 from the second-order condition.

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fident in drawing (correct) conclusions about the quality in the market, the "demand" curve becomes steeper. Thus, within the context of this extended model, improved precision in learning about quality maps into higher quality. That is, a potential explanation for part of the variation in quality we observe across sellers is that farmers' ability to infer quality differs across locations.

Taken together, the results show that high dilution rates will be found out quickly. As a result, farmers would not buy fertilizers of too low quality and the incentives to sell these highly diluted fertilizers should be weak. On the other side of the spectrum, it is difficult and takes time for farmers to accumulate evidence that authentic or close to authentic fertilizers are sold, when that is in fact the case. This implies that it will take a long time for sellers to build up a reputation as a high-quality retailer and price their products accordingly. At the same time, as profit margins are presumably in some way related to the rate of dilution of fertilizer, sellers likely have strong short-run incentives not to sell high quality. In fact, given the unregulated and unmonitored market structure and the difficulty farmers face in learning about profitable fertilizers, the question may not be why we observe widespread dilution of fertilizers on the market but why any seller would supply profitable fertilizers without a markup, which we do observe. The answer is likely that at least some sellers have important intrinsic and nonpecuniary motivations not to sell inputs of too low quality. Finally, consistent with the evidence from the farmer survey, we have shown that the market does not collapse. Some farmers do buy. In the model they do so because they either have managed to purchase profitable fertilizers or because they are overly optimistic after receiving (a series of) positive yield shocks.

2. A Market for High Quality? Having focused on explaining the market as is, we now move to a more hypothetical question: what would happen if a seller committed to high quality entered the market and started selling fertilizer to farmers, in particular, to the farmers surveyed in our study. Assuming that farmers are Bayesian, and given the farmers' (initial) distribution about quality, we investigate whether a seller committed to high quality would be able to build a reputation for selling profitable fertilizer and price its product accordingly, under the status quo and when additional constraints that might improve the learn-

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ing environment are lifted. This is an interesting counterfactual policy question because a potential intervention to overcome the lemons problem in the market for fertilizer could be the entry of a nongovernmental organization (NGO) or a private firm that sells the highest possible quality, not necessarily at a subsidized price and without a strong reputation to begin with. Thus, we are interested in understanding how beliefs, willingness to pay, and adoption would evolve over time given existing (prior) beliefs among farmers in our data.

We determine the rate of learning about authentic quality and what farmers are willing to pay for such quality by letting each of the N farmers in our survey experiment for T periods with authentic fertilizer.[28] For each farmer, we derive the prior density of dilution rates from her reported distribution of fertilizer quality in the nearest shop. Following each round of experimentation, the farmer receives an unbiased signal with standard deviation σ_ε about fertilizer quality, where we use either the estimate from the experimental data as before or a 50% higher level to account for additional uncertainty at the farmer level. The farmer updates her posterior density according to Bayes law, and we can then use this density to calculate the distribution of confidence and the willingness to pay for authentic fertilizer in the sample of farmers we surveyed.

Consistent with the previous analysis, being confident that fertilizer is profitable takes time even for the slightly more optimistic farmers in our survey. After five rounds of experimentation, only 16% of farmers have strong evidence in favor of profitability. This number is even lower (less than 1 in 10) if the noise experienced by farmers is larger than the benchmark estimate (Online Appendix Figure A.4). Similarly, few farmers are willing to buy, at least initially: only one in five has a willingness to pay above market price after experimenting once, and this drops to less than 1 in 10 if learning is even noisier. Although this number rises to 70% and 50%, respectively, after five periods of experimentation, the average willingness to pay only just exceeds market price at this stage and the average margin for those with a willingness to pay above market price is roughly half of that which would obtain

28. To account for some quality shortfalls even from a seller committed to high quality, we assume that fertilizer quality is uniformly distributed on the "almost authentic" interval $\theta \in [0, 0.1]$.

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if quality was known with certainty.[29] Hence a seller committed to high quality could potentially establish themselves, but only if they are in it for the long haul. Moreover, such a seller could either capture a large share of the market or raise prices, but would struggle to do both.

Our analysis so far is based on a set of parameters estimated directly from the data. Importantly, several of these parameters are determined by factors we do not study here but that relate directly or indirectly to several constraints to adoption that have been highlighted in the recent literature. For example, lack of information about optimal agricultural practice and the use of the technologies has a direct effect on profits and thus the farmers' willingness to adopt.[30] It may also affect the variability in returns to adoption (or to farming in general) and thereby farmers' ability to infer quality.

Learning about quality would in principle also be enhanced by combining more information sources, that is, through social rather than individual learning.[31] Observing technology choices and yield from other farmers will increase the number of signals a farmer would receive at each point in time and thereby speed up the process of learning about quality. However, as the signal-to-noise ratio when learning from others is affected by the heterogeneity in plot characteristics and especially farmer characteristics (Munshi 2004), it may also complicate the inference problem.[32]

29. Adding uncertainty to the realization of yields for a given dilution level when going to scale (see Section VII.A) lowers the willingness to pay even further (see Online Appendix Figure A.3), although the fall in the *WTP* is relatively small.

30. Duflo, Kremer, and Robinson (2006) show that intensive extension work significantly increased the use of fertilizers, although the quantitative effects were quite small.

31. On social learning about expected yield, see, for example, Besley and Case (1994) and Munshi (2004). On social learning about optimal input application, see, for example, Foster and Rosenzweig (1995), Conley and Udry (2010), and Duflo, Kremer, and Robinson (2006). The empirical evidence is somewhat mixed, with Foster and Rosenzweig (1995) and Conley and Udry (2010) showing evidence in favor of social learning, whereas Duflo, Kremer, and Robinson (2006) show that information from neighbors plays a very limited role in decisions about fertilizer use.

32. The less a farmer is able to observe actions and characteristics of her peers, the more difficult it will be for her to accurately assess the available information, and the more likely that she makes mistakes.

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Both fertilizers and hybrid seeds are divisible and standard theory does therefore not predict that credit constraints can explain why farmers do not use these technologies at all.[33] Liquidity and risk constraints, however, do not only have a potential direct effect on farmers' willingness to adopt but could also affect farmers' ability to learn about quality by forcing farmers to experiment at small scale—as we assume in our learning model.[34] Having access to insurance markets and not facing any liquidity constraints should allow farmers to experiment on a larger plot. This in turn will likely attenuate some of the measurement error in the signal equation (3) and thus increase the signal-to-noise ratio.

Assuming the relaxation of credit, liquidity, and information constraints increases the signal-to-noise ratio, we can home in on one potential mechanism through which the relaxation of these constraints may impact the market for high quality. Specifically, we repeat the analysis of letting the farmers in our survey experiment for T periods with authentic fertilizer but reduce the noise on the quality signal.

If farmers could experiment in a less noisy environment, confidence about quality and therefore the seller's ability to price her products appropriately would increase faster (Online Appendix Figure A.4): with noise equivalent to 50% of the original standard deviation, half the farmers would have strong evidence that fertilizer is profitable after five periods of experimentation and 90% would have a willingness to pay above 1, with the average margin around two thirds of that obtained under certainty. Of course, this margin in turn is constrained by the relatively high required rate

33. This no longer holds if there are fixed costs to adoption, for instance, fixed costs in buying the inputs. Such fixed costs would have to be implausibly large, however, to justify the lack of investment in fertilizers and/or hybrid seeds in the standard model (see discussion in Duflo, Kremer, and Robinson 2011). Experimental evidence on technology adoption in agriculture suggests that credit constraints are not a binding constraint for most farmers. Financial barriers, however, go beyond a lack of credit access. Karlan et al. (2014) find substantial demand for index insurance and a strong effect of insurance on agricultural investments. Duflo, Kremer, and Robinson (2011) show that providing farmers with a commitment savings technology substantially increased fertilizer use.

34. Farmers may be forced to experiment with modern inputs on a small plot due to credit and cash constraints. They may also choose to experiment on a small scale for other reasons. The *WTP* based on the priors for most farmers in the sample is below 1. Farmers might thus consider buying for a small part of the field to reduce their uncertainty about profits, that is, low profitability and high uncertainty may also constrain the scale of experimentation.

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of return on fertilizer. Inasmuch as access to insurance and credit markets would reduce the required rate of return, the potential profits of the seller and hence the incentives to sell authentic fertilizer would increase even further.

To sum up, the results with a higher signal-to-noise ratio suggest that by addressing constraints we know are limiting farmers' willingness to adopt modern technologies, one can, through affecting the speed and strength of learning and thereby sellers' incentive to supply high quality, also potentially mitigate the market for lemons problem in agricultural input markets.

VIII. Discussion

We find that the quality of fertilizers and hybrid seeds sold in local markets in two of the main maize-growing regions of Uganda is low on average. Moreover, under reasonable assumptions on costs, the return to adoption of such substandard inputs is low. The rate of return of using authentic fertilizer and hybrid seed is large, however. Together, our results suggest that one reason smallholder farmers do not adopt fertilizer and hybrid seeds is that the technologies available in local markets are simply not very profitable.

We further provide evidence of the learning environment facing smallholder farmers, showing that farmers can likely infer that inputs are of poor quality if the quality of the inputs is sufficiently low, but they find it hard to detect whether the large majority of substandard fertilizers observed in the market place are profitable. Moreover, we argue that the sellers' pecuniary incentives to build up a high-quality reputation are likely weak, as farmers cannot distinguish authentic from slightly lower quality and farmers' willingness to pay falls relatively little as quality falls, at least starting at low levels of dilutions. This finding may help explain why we do not observe sellers selling high quality at a premium price.

Our findings imply interesting avenues for future research. Low quality could be due to a multitude of factors, including adulteration, poor storage, and inappropriate handling procedures. Moreover, quality deterioration could manifest at different points in the supply chain. Anecdotal evidence and news reports suggest that adulteration, by bulking out fertilizer or dyeing simple grain to look like hybrid seeds, is common, but more research is needed to determine if this is indeed the case. Although the exact reasons

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may be irrelevant for a farmer's decision to adopt, understanding the determinants of quality is important for policy.[35]

More generally, our findings highlight the need to identify ways to substantially increase the quality of basic agricultural technologies available to smallholder farmers. An obvious follow-up question to our work is how the rate of technology adoption and productivity would change if smallholder farmers could access high-quality inputs and whether adoption rates could be further boosted by addressing other binding adoption constraints as our analysis suggests.

The low technology adoption rates in Sub-Saharan Africa are probably caused by several interrelated factors, as the recent experimental literature has shown. Importantly, even if farmers' decisions whether to use fertilizers and hybrid seeds are not primarily constrained by the low quality of the technologies in the marketplace, low quality has a first-order impact on the income and welfare of smallholder farmers who adopt. For adopters we estimate that the loss in revenues, per hectare of land, due to substandard quality, is US$250 on average, that is, for average market quality, per season. As a reference, the revenue from traditional farming, the main source of income for poor smallholder farmers, per hectare of land and season, is estimated to be just over US$320.

Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

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35. Agricultural technologies such as fertilizer and hybrid seeds form part of a wider set of products or inputs where quality is not directly observable at the time of purchase, and only partially observable when used. Anecdotal evidence and news reports suggest that product quality in markets for experience goods more broadly is notoriously low in developing countries. Recent work on poor-quality medicine in developing countries is a case in point (see, e.g., Bjorkman-Nykvist, Svensson, and Yanagizawa-Drott 2012; Bennett and Yin 2014).

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