Restoring Trust: Evidence from the Fertiliser Market in Tanzania

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A lack of reliable information about fertiliser quality depresses farmer demand, reducing crop yields and negatively impacting livelihoods. We implemented a randomized controlled trial across 100 market clusters and 148 associated villages in an agricultural region of Tanzania. Fertiliser sellers and farmers in the treatment market clusters received a low-touch information campaign consisting of posters, pamphlets, and meetings explaining that urea fertiliser tested in their markets was found to be of good quality, with the required amount of nitrogen. We find evidence of substantial concerns among farmers regarding the quality of urea fertiliser at baseline, with 80% of farmers reporting beliefs that fertiliser is of bad quality. The information treatment significantly improves farmer beliefs about fertiliser quality and reduces variance of beliefs across farmers within treatment villages. Treated farmers buy more fertiliser. We show that retailers in treated markets report increased sales but stable prices.

Keywords: Fertilizer; Technology Adoption; Trust; Sub-Saharan Africa; Beliefs; Credence Goods

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1 Introduction

The functioning of rural markets is critical to technology adoption and economic growth in low income countries. Trust in product quality is essential to economic transactions. Farmers in developing countries purchase pesticides, fertilisers, seed and other inputs from small shops in a largely unregulated environment. All of these critical inputs into agricultural production have unobservable key attributes. A lack of trust in product quality can lower purchases, and consequently use of profit-enhancing technologies and inputs (Gilligan and Karachiwalla, 2021; Bulte et al., n.d.). This issue is not unique to agricultural production inputs. A lack of trust in product quality impacts the demand for other important goods in low income countries including health products (Björkman Nyqvist, Svensson and Yanagizawa-Drott, 2022; Adhvaryu, 2014), education (Dulleck and Kerschbamer, 2006), food retail (Bai, 2021), and crop output markets, (Park, Yuan and Zhang, 2022; Fuller and Ricker-Gilbert, 2021; Anissa et al., 2021).

This paper uses an information campaign to improve trust in product quality and to study the effects that improving trust can have on buyers and on suppliers. Markets that lack trust, where buyers have doubts about product quality, have higher transactions costs, as consumers must expend more effort and time in evaluating commodities they need. A market with trust frictions is often characterized by reduced market participation and investment, depressed demand, and distorted allocative efficiency.

We combine an information intervention in rural Tanzania designed to restore trust in a key farm input - fertiliser - with detailed panel data on beliefs, purchases, and sales collected from a representative large sample of farmers and all shops within one agricultural region over the course of a year. Our design allows us to estimate the impacts of the information intervention on farmers' trust and purchases, as well as the effects on the shops and markets. We selected Tanzania as the site of our study. Farmers in Tanzania use too little fertiliser, between 15 and 20 kg per hectare, significantly below recommended amounts (World Development Indicators, 2021). A large body of literature has established the high, albeit heterogeneous, marginal returns to increasing fertiliser use (Kaliba, Verkuijl and Mwangi, 2000; Marenya and Barrett, 2009; Chivenge, Vanlauwe and Six, 2011; Beaman et al., 2013; Suri, 2011; Liverpool-Tasie et al., 2017; Hurley, Koo and Tesfaye, 2018).

The agronomic quality of fertiliser is determined by its nutrient content; nutrient content cannot be directly visually observed and cannot be easily learned within the stochastic production environment in which farmers operate (Bold et al., 2017; Hoel et al., 2021). In Michelson et al. (2021) we document that farmers believe that local dealers tamper with the quality of fertilisers or allow them to degrade. This stands in sharp contrast with the results of the fertiliser tests we conducted in that study: we find that less than 1% of urea fertiliser samples tested had less than the required 46% nitrogen.[1] This result is consistent with numerous studies from the region (Sanabria, Dimithè and Alognikou, 2013; Sanabria et al., 2018*a*,*b*; Hoel et al., 2021; Ashour et al., 2019). The body of evidence regarding tested fertiliser quality is summarized and discussed in Michelson, Gourlay and Wollburg (2022).

We partnered with Tanzania's Sokoine University of Agriculture (SUA), a local and well-trusted, public university commonly engaged in extension activities. This partnership was essential to the success of the project, as it instilled confidence and trust not just in our research activities, but in the information interventions we rolled out to farmers and sellers. We randomly assigned all markets in the Morogoro agricultural region of Tanzania to either a treatment group or a control group. We randomly selected 148 villages near these markets, and assigned villages close to treatment markets to treatment and villages close to control markets as control. Retail shops which sell fertilisers, called agro-dealers in the region, belonging to the treatment group received pamphlets and posters with the message that the urea tested in that market was of good quality. We held in-person information meetings in the 75 villages near the treatment markets informing them that fertiliser quality

[1] Urea is the most widely stocked and sold fertiliser by retailers in Tanzania (Benson and Mogues, 2018) and also the most commonly used fertiliser in Tanzania. It is 46% nitrogen by weight and among the most important fertilisers for plant development. Other commonly available fertilisers in Tanzania include diammonium phosphate (DAP), calcium ammonium nitrate (CAN), and nitrogen-phosphorous-potassium fertiliser (NPK).

was good. We collected data among village farmers and all agro-dealers at baseline and post-intervention. We took messenger effects seriously (Cilliers, Dube and Siddiqi, 2015): we split off the enumerator team from the intervention team, sequenced the work, and made sure our teams were visibly associated Sokoine University.[2]

We find that farmers' concerns about fertiliser quality are considerable. At baseline, 80% of farmers report concerns about urea fertiliser quality, as measured by a probability-framed market-level elicitation mechanism. Farmer concerns change in response to the village information sessions, which reduce the probability of having any concern by 12%, and reduces the average level of concern by 16%. However, even though we had a close to 100% participation in the sessions, not all farmers were convinced: 50% of farmers in the treatment villages report concerns at endline. Due to this heterogeneity in response to the treatment, within-village dispersion in beliefs increases in the treatment villages.

The village information sessions increase the probability of using urea fertiliser by 10 percentage points, an effect size of 27%. This effect is largely driven by new fertiliser users. Fertiliser use per acre increased by 5.6 kg, an effect size of about 46%.

Effects are confined to use of urea fertiliser, without spillovers to other inputs. We do not observe any positive effects on the use of non-urea fertilisers. We note an increase in the use of hybrid maize seed, a well-known complementary investment, but not on other inputs, such as pesticides. We note no statistically significant effects on maize yields nor farmer beliefs about maize yields.

Using both farmer and agro-dealer data, we find no effect of the information treatment on market prices. Prices are regulated by the government, and our qualitative interviews confirm that agro-dealers worry about enforcement of these prices. Similarly, we find no effect on the likelihood that treated agro-dealers sell urea fertiliser. As almost all agro-dealers sell urea at baseline, and the lack of effects on the external margin is to be expected. We use a Bayesian hierarchical model to test for the effects of the information treatment on

[2]One year after our intervention, and after having established positive effects, we rolled out our intervention the control markets. See the Ethics Appendix for discussion of these and other points.

sales. We find sizable impacts on the quantity of urea sold, an effect size of almost 5%.

We begin by describing the relevant background in Tanzania: details related to the fertiliser market and government policies. Section 3 presents the sample and randomization and Section 4 describes the information treatment. Section 5 explains the data sets: the farmer survey, the agro-dealer survey, and agro-dealer calls conducted within the major sales season and presents descriptive statistics for the samples. Section 6 presents analysis and results and Section 7 concludes.

2 Background

Fertiliser use is low in Tanzania. Tanzania's National Bureau of Statistics (2020) found that only 2.5 million hectares, equivalent to 21.4 percent of total planted area, were cultivated with fertilisers in the 2019/2020 production season. Most cultivated land in Tanzania is characterized by low fertility, with nitrogen a primary limiting nutrient (Marandu et al., 2014) but other widespread nutrient deficiencies include phosphorus, potassium and sulfur, copper, zinc, and magnesium. While the Tanzanian government recommends application of 100 kg of nitrogen and 40 kg of phosphorous for one hectare of maize cultivation Kohler (2020), current fertiliser use is reported to average 17 kg/ha/year (World Bank 2014). Rates are even lower in Morogoro - less than nine kilograms of fertiliser per acre (IFDC 2012). Most smallholders in Tanzania do not use fertilisers; among those who do use fertiliser, application rates are generally far less than recommended (Senkoro et al., 2017; Ariga et al., 2019*a*).

Tanzania imports nearly all of its fertiliser in bulk through the Dar es Salaam port. Fertiliser then makes it way inland from the port through a network of wholesalers and is sold to farmers in local markets by retail shops. These shops, commonly known as agro-dealers, sell other agricultural inputs, and can also serve as informal credit-providers, information points, and buyers of agricultural output (Tadesse and Shively, 2013). Small farmers tend to purchase small amounts of fertiliser at a time, one to two kg scoops from open 25 or 50 kg fertiliser bags.

All fertiliser activities in Tanzania are subject to Tanzania's Fertiliser Regulations Act of

2011, which states that no fertiliser or fertiliser supplement shall be used in Tanzania unless it has been sampled, tested, analysed, evaluated and recommended for use overseen by the Tanzania fertiliser Regulatory Authority (TFRA). The TFRA is underfunded however, and little regulation of the market takes place in actuality.[3] In accordance with Tanzania's Fertilser Regulations Act, all dealers and premises must be registered; all fertiliser importers and exporters must acquire a special permit.

It is well established that farmers are suspicious of the quality of fertiliser in their local markets (Bold et al., 2017; Ashour et al., 2019; Sanabria, Dimithè and Alognikou, 2013), especially in the Morogoro Region of Tanzania (Michelson et al., 2021; Michelson, Gourlay and Wollburg, 2022). Concerns about quality are reinforced in the media (Kasumuni 2016), though work by our research team in 2018 investigating the journalistic sources of several articles in the national newspaper The Citizen reporting on counterfeit fertiliser for sale in the country found that the stories themselves were based on rumors.

What's puzzling about this widespread perception of uncertain fertiliser quality among farmers is that it does not seem to reflect the truth. Despite widespread evidence of farmer suspicion about fertiliser quality, research has also now convincingly established that the agronomic quality of fertiliser in the region, especially urea fertiliser quality, is good (Sanabria et al., 2018*a*,*b*; Michelson et al., 2021). This body of evidence regarding the documented quality of fertilisers is summarized in Michelson, Gourlay and Wollburg (2022). One likely reason for little fertiliser tampering (either adulteration or full-scale counterfeiting) is that it is difficult to do profitably: the cost-benefit from this action generally does not add up on the seller side.

The market failure we address in this paper relates to the lack of trust in this market

[3]While the TFRA is the primary government agency with regulatory mandate over fertiliser product quality, other government agencies overseeing aspects of the fertiliser sector include the Weight Measures Agency (WMA), the Tanzania Atomic Agency Commission (TAEC), and the Surface and Marine Transport Regulatory Authority (SUMATRA). These actors are tasked with enforcing quality and standards related to fertiliser importation, distribution, storage, and marketing (URT, 2009). The involvement of multiple regulatory agencies in the fertiliser industry has been cited as a source of high compliance and business costs for the sector.

characterized by unobservable product quality and limited regulatory enforcement. Farmers are aware of the lack of enforcement, and any concerns about quality can be reinforced by media (Kasumuni 2016) and the suspicions of others.

In a previous study conducted in 2015/16 we documented that farmers often believe that local dealers tamper with the quality of fertilisers or that they allow it to degrade (Michelson et al., 2021). This lack of trust needs to be viewed in a broader context. Tanzanians report low trust in their government, in their institutions, and in each other (the latter is called generalised trust). Data from the Afrobarometer and the World Value survey, presented in Table 1, reveals that farmers believe that corruption is highly prevalent, and that the government is not doing enough to address corruption. Notably 46% do not trust vendors when it comes to providing the correct amount of seed (see Sapienza, Toldra-Simats and Zingales (2013); Etang, Fielding and Knowles (2012); Glaeser et al. (2000) for further interpretation).

In the same study we purchased urea fertiliser from all agro dealers in the region using mystery shoppers and tested the fertiliser samples in laboratories in the United States and Kenya. We established that fertiliser quality was excellent across markets, with the required amount of nitrogen. In this paper we again focus on urea fertiliser, which is the most important fertiliser both in quantities sold as well as in terms of plant growth and development. In this case, good quality implies containing 46% nitrogen by weight. Our previous results indicated that less than 1% of urea fertiliser samples tested had less than 46% nitrogen (Michelson et al., 2021) and then only trivially so, suggesting small deviations in manufacturing as the cause.

Our previous research therefore establishes evidence of an information friction in these markets (Michelson et al., 2021). Hoel et al. (2021) show that beliefs about bad quality urea can persist and farmers can fail to learn about true quality if farmers missattribute a bad yield outcome to bad quality fertiliser rather than to bad weather, incorrect or insufficient application.

Evidence suggests that these suspicions may reduce the demand of farmers for urea fertiliser. Michelson et al. (2021) and Hoel et al. (2021) show that farmer suspicions about fertiliser quality in Tanzania lower willingness-to-pay for fertilisers (relative to circumstances where the farmers are confident about quality). Other concurrent studies document similar effects on willingness-to-pay other inputs in other African countries (Gharib et al., 2021; Maredia et al., 2019).[4] In those markets where farmers have pessimistic beliefs about quality and associated lower willingness-to-pay, the demand curve for fertiliser could shift inward, decreasing fertiliser demand.

3 Sample and Randomization

3.1 Agro-dealers census and farmers sample

Building on our previous work in Michelson et al. (2021) we selected the Morogoro Region as the study site. Self-employment in agriculture provides the main income stream to households, and supports nearly all household activities. Smallholder agriculture accounts for 80-90% of the region's economic activity (Mutabazi et al., 2015). Most families consume what they grow, trade goods for other necessities, and sell their crops or livestock for income (EDI, 2007).

We started with the list of 100 markets previously identified in the fertiliser census conducted in Michelson et al. (2021) in 2015/16. While we started with the 2015/16 list, we again worked to identify all agro-dealers in operation in the region, surveying all shops selling agricultural inputs at our baseline in early 2019 and once again at endline in early 2020.[5]

Table 4 gives an overview of the agro-dealer sample. Of the 429 agro-dealers identified at both baseline and endline of our 2019/2020 study, only 233 were interviewed in both rounds. As this is a census, this represents considerable market churning (or possible errors on the

[4] See also Prieto et al. (2019) for evidence on the maize market.

[5] This approach at baseline resulted in the inclusion of some shops who had never sold and had no intention of stocking or selling fertilisers. We corrected this at endline and defined the eligible set of shops as those who were currently selling fertiliser, had sold fertiliser the previous year, or were planning to sell fertiliser in the future.

part of our research team). Data collected at endline indicates that the market churning is largely due to new shops opening, others closing, a handful of shops opening only for certain weeks of the year (during the main agricultural season early in the year), and some shops relocating.[6]. Overall, at baseline, we identified 89 markets where we interviewed agro-dealers while at endline this number was 85.

Our baseline data collection included the GPS location of each market. Figure **??** indicates the location of the markets. We worked with government extension officers to locate all villages within a 3 to 7 km ring surrounding the market. The 3 km minimum boundary ensured that farmers who were located within the immediate market boundaries themselves were excluded, avoiding a situation in which the market treatment and village treatment duplicate each other in the same location. The 7 km upper boundary ensured that the link between the village and the associated market was meaningful, meaning it would be feasible for the villagers to visit the market.

We randomly selected 148 villages from this full list of villages (we had aimed to select 150 villages, but not all markets had sufficient villages within the 3-7 km ring). As we have 100 markets, this implied that half of the markets had two accompanying villages while the other half had one associated village only (this process was stratified by treatment/control status of the market, and randomized by market).[7] So some markets are linked with two villages, while others only one. We refer to this linkage between the villages and their "associated" markets. Figure 3 shows the result of this randomization process. In practice, the villages selected do not always fall within the intended radius.

The household sample consists of ten randomly selected households from a household census list for each village obtained from the government agricultural extension officers.

[6]The redefinition of what constitutes an agro-dealer did not contribute substantially to this. See 7

[7]As the rings of some markets overlap, we randomized the sequence for this process, and a village is only linked with one market in the data.

3.2 Randomization

We randomized half of the markets into the treatment group and the other half into a control group. The treatment markets received the market intervention treatment immediately after the baseline interviews, while the control markets received the same treatment after the endline. Each village was also assigned a treatment status, with 74 villages (out of 147) in the treatment group. If the village was within the 7 km radius of only one market it was assigned the treatment status of this market, which necessarily would have been the "associated" market. If the village was within a 7 km radius of more than one market, and these markets had the same treatment status, the village was assigned the same treatment status as the markets. Matters became more complex in case a village was located within the 7 km radius of more than one market, and these markets were of different treatment status. In this case, we used a probability-based rule to assign status.[8]

It is important to emphasize that the treatment assignment of markets and villages was not cross-randomized.

The design "doubles-down" on the treatment. That is, all treated villages are associated and proximate to treated markets. While this method does not allow us to consider the cross-treatment effect of the village and market treatments, we preferred this method for three reasons related to statistical power and policy relevance. First, with only 100 markets in the region, power calculations at baseline suggested that we would be unlikely to pick up effects on beliefs, purchasing, or use using cross-randomization. Second, the village treatment becomes more credible to treated farmers: villagers who were informed about the treatment could see the posters in the market about which we informed them. Finally, the design also avoids some of the immediate spill-overs one would expect from treated markets to control villages (even though, as discussed in the Appendix, we were not entirely able to avoid all such spill-overs).

[8] The status of the village was allocated as per a Binomial distribution which followed the same probabilities as the nearby market. For instance, if 1 out of 3 nearby markets were treatment, the village was assigned as a treatment village with probability p = 1/3.

4 Intervention

We designed our intervention to provide to farmers and agro-dealers the information we generated about fertiliser quality in our previous research project (Michelson et al., 2021). The prior project used mystery shoppers to visit all fertiliser selling shops and markets in the Morogoro (in 2015 and 2016). We purchased fertiliser at these shops multiple times and tested these fertiliser samples in laboratories in Kenya and in the United States. Results showed that the the urea was excellent quality: 46% Nitrogen as required by international and regional standards.

Our intervention in this project consisted of two components: a market-level intervention and a village-level intervention. Both interventions were implemented in the two months between December 2018 and January 2019, after the baseline data collection. To facilitate the separation of intervention and data collection interviews, we had two separate teams on the ground. One team conducted the interviews, and one team conducted the intervention, with the interviewing team always arriving and finishing their activities prior to the intervention team.

We worked to ensure the information treatments were provided by a credible source in an official manner. One of the authors of this study is a professor at Sokoine Agricultural University, the most well-known agricultural university in Tanzania with a well established local and regional extension reputation. In addition, our university researchers worked together with local government extension agents to develop and implement village meetings that were consistent in their execution with the kinds of village presentations that are frequently used in extension. We produced and distributed pamphlets and posters to convey information about fertiliser quality, and we allowed sufficient time for questions and discussion in our meetings with villagers and our interactions with agro-dealers.

We present the timeline of the intervention in Figure 1. We present the intervention script and materials in the Appendix.

4.1 Market intervention

We began in the markets by verbally informing the agro-dealer about the results of our prior research study using a standardised script: explaining that that the urea fertiliser we had tested in the market in 2015/16 was of excellent quality. We then inquired as to whether we could hang a poster in the shop's window which contains this information, and whether we could leave a stack of pamphlets which the agro-dealer could distribute to their customers about the good quality urea rest results. To avoid strategic behavior on the part of the agro-dealer, we also noted that we would be testing the fertiliser again in 2019. None of the agro-dealers refused the posters or pamphlets. For each market, we provided eight posters and 100 pamphlets to be distributed among the agro dealers. In addition, we hung one poster in a central, prominent location in the market. We did not approach any customers in the markets, but if approached while posting the poster and distributing the pamphlets we explained our purpose following the same standardized script, and we shared a pamphlet with the individual making the inquiry. This happened quite often, as business continued as usual while we were in the shop.

We rolled out the same treatment to the control markets after the completion of the endline interviews between December of 2019 and January of 2020.

4.2 Village intervention

We invited all farmers in the village to a common location, such as outside the village office.

We informed the attendees about the good results of the urea fertiliser quality tests we had conducted. We used a standardised script to relay this information. We focused the information session on tests conducted on fertiliser from the local market. Recall that the village intervention linked up to the market intervention, with village treatments designed to reference and building on the local market intervention. Hence, the farmers in the village were informed about the quality of fertiliser in the local, associated market.[9] At the end of

[9] That is, if this associated market was a treatment market, which was mostly the case. In the exceptional

the session, the research team answered questions. We answered any question truthfully; if farmers asked about fertiliser quality in other markets, we explained our test results in those markets. All urea in all the markets had tested as good, so revealing information about fertiliser quality in other markets meant that we conveyed that fertiliser in that market was also excellent. At the end of the village treatment meeting, we also left pamphlets with the villagers; around 135 pamphlets per village.

5 Data

We collected data from farmers and agro-dealers before and after the intervention. Both farmers and dealers were visited in person at baseline. The endline farmer data has two components: phone data collected in Fall 2019 for the full sample and in-person data collected in Spring 2020 with a sub-sample of villages. Survey teams visited the agro-dealers in person in Spring 2020 for the endline survey. Figure 4 presents an overview.

5.1 Farmer survey

We interviewed the primary decision-maker regarding agriculture in the household for the farmer interviews. We defined a household as individuals eating from the same kitchen on a daily basis for the last six months (excluding newborns). Baseline was conducted in person and endline was conducted in two ways: first, by phone for all households and villages and then in person for a subset of the villages - 29 (out of 148) villages. The farmers received a payment of 5000 TZS for the endline phone interviews. The main panel results are therefore based on the panel comprised of the baseline and phone-based endline. The in-person endline does not constitute a part of the main panel.

We collected baseline data on respondent and farm characteristics: age, sex, education, risk aversion, and land ownership. At baseline and phone-based endline we collected farmer fertiliser beliefs, purchases and use. The in-person endline further asked about the sources of information, the perceptions of the village intervention and market intervention (which

case that the associated market of a treatment village was a control market, the attendees were informed of the quality of fertiliser in the nearest treatment market markets they had visited in the past growing season and whether they had seen any of our posters there) and details related to their maize production.

A primary contribution of our project and data collection is the panel data on fertiliser beliefs and fertiliser purchases. Combining the in-person baseline survey with the phone endline survey, we compose a market-level panel data set on fertiliser beliefs and purchases.

Beliefs about fertiliser quality To measure beliefs about fertiliser quality, we asked farmers to consider three different markets, one at a time. We asked, for each market: "If 10 farmers, like you, purchase one 1 kilogram bag of urea fertiliser at [this market] this week, how many would be bad quality and how many would be good quality?" This type of formulation, as opposed to a probabilistic statement, did well in pretesting, as farmers commonly purchase 1 kg of fertiliser, which they would then judge to be either of good quality or of bad quality (see also Hoel et al. (2021), and Ashour et al. (2019) for a similar approach).[10] Preceding this question, the enumerator discussed with the farmer that good quality related to the correct amount of nitrogen in urea (i.e., 46% by weight),[11] We had pre-selected the three markets to include the three nearest markets to the village, one of which was the associated market for the information intervention.[12] Results in Kerwin and Ordaz Reynoso (2021) suggest that knowledge from the interviewer can spillover to respondents in in-person survey-based belief elicitation; our enumerators were trained before the baseline village meetings and so such an affect is likely to have increased belief in the fertiliser being good across both treatment and control groups at baseline. Note that Kerwin and Ordaz Reynoso (2021) are focused on

[10]Beliefs elicitation is common in agricultural economics and development economics. We build on Grisley and Kellogg (1983); Lybbert et al. (2007); Bonan, Kazianga and Mendola (2020); Maertens (2017); Delavande (2023) and the overview studies by Delavande, Giné and McKenzie (2011) and Delavande (2023) to elicit the beliefs regarding fertiliser quality during the baseline interviews and endline phone interviews.

[11]The exact formulation was: "Fertilisers, including urea, have nutrient and moisture standards that ensure that the fertiliser will preserve or improve soil fertility and help the crops to grow. For example, in urea, the most important element is Nitrogen and samples of urea should contain 46% nitrogen. For the purposes of the following questions, "good quality" will mean urea fertiliser that has the amount of nitrogen that it is supposed to have: 46% nitrogen."

[12]The pre-filled endline questionnaire contained errors among some farmers and presented them with duplicate markets. For 28 farmers these data were not be used as respondents indicated conflicting responses to the same market, possible referring to distinct purchasing experiences.

beliefs about HIV transmission rates and risk taking behavior among respondents, a topic of a more more sensitive and personal nature than fertiliser.

Fertiliser purchases All fertiliser purchase questions refer to the previous long rains season, which starts in February and lasts through June. We asked farmers about their purchase and use of six different relevant fertilisers: Urea, NPK, DAP, Minjinju, CAN and SA. At baseline (referencing the 2018 season), we asked the farmer how much of each fertiliser type the household had purchased, and where the household purchased the fertiliser, allowing for multiple markets per fertiliser. If the respondent stated that the household used fertiliser, we gathered information about the acreage cultivated, area fertilised, and crops to which the fertilisers were applied. The endline phone survey also inquired about fertiliser purchases during the previous (2019) long rains season and the price paid (per kg).

Market visits and information At baseline, we asked the farmer about the markets he/she visited in the past twelve months prior to the interview. During the endline phone survey, we asked the farmer whether they had visited any of the three nearest markets, and if so, whether they had seen any of our posters or pamphlets there, or received information on these markets during our village intervention meetings.

5.2 Agro dealer survey

We aimed to interview the shop-owner in these interviews. If the shop-owner was not available, another knowledgeable member of staff was interviewed. We collected baseline data on business locations, shop and owner characteristics, asset ownership and asset rentals, stock facilities and current stocks, supply chains and characteristics, and sales. We also conducted a series of in-person observations, detailing visible inventory, posted certifications, number of employees, and number of customers present at the time of interview.[13] In the endline interviews, we collected a second round of data on stock facilities, current stocks and sales.

[13]At the endline, we collected information on business location, shop and ownership characteristics, assets ownership and asset rentals for those business which were new in the market, or not interviewed at baseline for other reasons.

We also inquired about the agro-dealer's perception of the market treatment, and repeated our in-person observations.

Sales: Quantities and Prices We focused on the same set of six fertilisers with the agro-dealers: Urea, NPK, DAP, Minjinju, CAN and SA. For each type, we recorded whether or not the dealer had ever sold it, whether or not the dealer had it in stock (at the time of the interview) and the total amount sold (in the previous calendar year). The endline interview also notes the price (at the time of the interview) for a 50 kg bag (including a market estimate from those dealers who did not have the fertiliser in stock at the time of the interview).[14]

WTP for intervention In the endline survey we inquired about the agro-dealer's willingness-to-pay for a fertiliser quality certificate (by Sokoine Agricultural University) similar to the information treatment provided in the RCT. [15] While we did not use a BDM mechanism, we made sure to emphasize that we were looking for the highest price they were willing to pay, and not what they thought such a certification would or should cost.

5.3 Descriptive statistics

5.3.1 Farmer statistics

Table 3 introduces the farmer analysis sample, the balanced panel of farmers surveyed at both baseline and (via the phone) during endline. This endline survey reached 995 of the 1,479 farmers interviewed at baseline. The 33% attrition rate is large but in line with other phone surveys in the area. In Appendix table A.1 we show that this attrition is not correlated with treatment status. Recall that the endline in-person survey was restricted to 30 villages. We use this in-person endline to validate the phone survey rather than to

[14]Due to the stringent enforcement of the fertiliser maximum prices, prices were a sensitive topic. It was for this reason that we avoided asking for prices at baseline, and only at endline, after having established a relationship with the dealer, asked about sales prices.

[15]We asked: "Imagine that Sokoine University could come and test your urea fertiliser and establish that the quality of the urea fertiliser meets official government regulations. Then, once this is done, the university would provide you with these types of pamphlets and posters (we show the pamphlets and posters to the respondent). What is the highest price you would be willing to pay for doing this type of test, today?"

establish treatment effects.

Column (1) of Table 3 presents statistics for the full panel, Column (2) contains for control villages only, and Column (3) the treatment villages. Column (4) presents the p-value of a t-statistic testing for differences between the means of the control and treatment villages. The majority of the farmers in the panel are male. The average age is 45 years, and their household includes 5.55 members. Farmers own, on average, almost 7 acres of land, and have 16 years of farming experience at their present location. The sample is balanced across the treatment and control villages, although farmers in treatment villages characterize themselves as slightly more risk-loving. We control for these baseline characteristics in our analysis.

The farmer sample can be divided into three categories based on their recent fertiliser purchase: 40% have never purchased fertiliser, 40% purchased fertiliser in the season prior to the baseline survey and 20% have purchased fertiliser before, but not in the season prior to the baseline survey. We find few meaningful differences between the control and treatment villages. Slightly fewer farmers in the control villages purchased any fertiliser last season, and there is an imbalance in DAP purchases. Urea is the most commonly purchased fertiliser, with 37% reporting that they had purchased urea in last growing season. Purchase and use of other fertilisers, NPK, DAP, and CAN, are significantly less common.

Conditional on purchasing fertiliser, 45% of farmers use it on all of their land, mostly applying it to rice paddy or maize. Yet, application rates are far below the amounts recommended for this region (recommendation is 60 kg urea and 40 kg DAP for an acre of maize). Figure 5 presents the distribution of the kilograms of fertiliser used (conditional on use and pooling across all fertiliser types) per acre of land. Again, 45% applied less than 20 kg/acre.

Farmers visit agricultural markets a few times each year, on average, between one to two market locations. Conditional on purchasing fertilisers, 85% of farmers purchases their fertilisers at just one market. Moreover, the market where farmers purchase fertiliser is typically visited only a few times each year.

In Appendix Table A.2 we present the correlates of fertiliser purchases and use.[16] Baseline purchases are associated with more land, and lower levels of risk aversion. Farmers who purchase fertiliser also report visiting more markets.

5.3.2 Agro-dealer statistics

Our main analysis sample consists of the balanced panel of agro-dealers present at both baseline and (in-person) endline interviews. Unlike the farmer sample, defining this analysis sample was more challenging as firms moved, went out of business and started up during the period of our project. Details on our definition are provided in Appendix Table A.4. Overall, attrition is substantial, 22% firms exited, primarily due to businesses closings and relocating (see Appendix Figure A.1). This attrition does not correlate with the market treatment (Appendix Table A.5), although treatment markets do appear to have more agro-dealers (Appendix Table A.3). We present a robustness check based on smaller sample, those agro-dealers which sell fertilisers in both periods (the seventh category in Appendix Table A.4).

Table 4 presents descriptive statistics for the full analysis sample in Column (1), Column (2) includes the control market agro-dealers and Column (3) the treatment market agro-dealers. To check for baseline balance, we conduct a t-test with unequal variance for selected baseline characteristics. We report the results in Column (4). Overall, the randomization was successful in balancing the two groups of sellers across these observable characteristics.

Most agro-dealers are male, and have secondary or higher education. Half of the shops have the required government TFRA license for selling fertiliser and a little less than 40% report membership in Tagmark, which was required for dealers to offer inputs to voucher recipients during Tanzania's NAIVS subsidy program (2008-2014). Most stores are only open a few months of the year, and this is particularly the case for shops in the treatment markets (though the difference is not statistically significant). The average number of years the agro-dealer has been selling fertiliser is 4.2 years. Conditional on the shops being open,

[16]The reduced sample is due to the use of village-fixed effects, and missing observations in some of the control variables.

not all fertilisers are stocked and sold. Our baseline interviews took place in December, January and February, i.e., the months just before the long rains planting, and almost half of the stores did not have any urea in stock yet, although most agro-dealers have sold urea in the past (about 70%). Significantly fewer reported selling other fertilisers: 42% had sold NPK, 40% sold SA, 51% sold DAP, 60% sold CAN, and 5% sold the local blend Minjingu. The average total amount of fertiliser sold per shop was about 18 tons in 2019; more than half of this quantity was urea.

5.3.3 Descriptive analysis of baseline beliefs

To measure beliefs about urea fertiliser quality, we asked farmers to consider three different proximate markets, one at a time (including the associated market). For the main analysis, we average the responses across the markets for each farmer to provide a measure of each farmer's belief. On average, farmers expect two out of ten bags in their local markets to be of poor quality, and 77% of farmers have concerns regarding quality (see Table 3). In an extension, we exploit the considerable variation across markets (within farmers).

We present the distribution in Figure 6: 22% of farmers believe that fertiliser in their local markets has no quality issues; the beliefs of the remaining farmers follow a roughly normal distribution.

Farmer concerns about fertilisers do not appear to stop fertiliser use altogether. Cross tabulations using the full baseline sample show that 60% of farmers who do not have concerns about urea fertiliser quality did not purchase urea in the previous season. Moreover, 40% of farmers who have concerns did purchase urea fertiliser. So concerns, or lack thereof, are neither a necessary, nor a sufficient condition for purchasing.

However, fertiliser quality concerns and lack of fertiliser use are correlated. In Appendix Figure A.2 we present a histogram of farmer beliefs about fertiliser quality by past experience with fertiliser. Having purchased fertiliser before exhibits a negative relationship with (1) whether farmers report any concern about quality and (2) the magnitude of the concern reported. We conclude the same from Appendix Table A.6 which maps the farmer beliefs onto farmer characterises at baseline.[17] The sizable R-squared is due to significant role of village fixed effects. It is notable that there are no villages in which everyone is unconcerned; in 10% of villages all farmers expressed concerns. These concerned villages are geographically concentrated in the area around the Morogoro hills, a more remote area where farmers have little experience with fertilisers.

5.3.4 Descriptive statistics of market-level choice and beliefs

We have so far presented statistics averaging farmer beliefs across the three markets for which we elicited their assessments. We can further dis-aggregate our analysis by market. While 75% of the variation in beliefs is at the farmer level, the variation between markets by farmer is substantial and suggests that beliefs respond to market-specific characteristics and experiences.

To shed more light on the role of these, Appendix Table A.7 presents the results of a series of market/farmer level regressions using beliefs as a dependent variable – again captured by the number of bad quality bags out of ten. Column (1) adds market-level characteristics, Column (2) adds information on visiting frequency, Column (3) adds information on past purchases at the market, and Column (4) combines all these characteristics. Columns (3) and (4) are conditional on having purchased fertiliser in the past. Note that all specifications control for the order in which the beliefs were elicited. Note also the smaller than expected sample size: While we endeavoured to include all farmers in the balanced panel, data quality limits our analysis as not all farmers were asked or provided beliefs estimates of the three preselected close-by markets, and in about 10% of cases no market ID could be attributed to the market.

While the result of these regressions need to be interpreted as correlations, we employ a farmer-fixed effect strategy to strengthen the possible causal interpretation. Results show that farmers express fewer concerns for larger markets (Column (1)) - as captured by the number of agro-dealers. Never having visited a market increases a farmer's concerns (Col-

[17] The reduced sample is due to the use of village-fixed effects, and missing observations in some of the control variables.

umn (2)), and purchasing experience improves quality expectations. Inspecting correlations between these various independent variables (and restricting the analysis to markets less than 50 km away due to a handful of significant outliers in the distance variable), we note that the larger markets tend to be further away from the homestead, and tend to have less market instability/churning or turnover (as measured by the ratio of agro-dealers selling in both rounds over all agro-dealer shops interviewed). As farmers tend to purchase fertiliser in larger markets, this suggests that farmers often travel quite far to purchase fertilisers (as opposed to the smaller markets near one's village that farmers often visits for other transactions).

In Appendix Table A.8 we present the results of a similar farmer fixed effects specification, this time with purchases at a market as a dependent variable. Note that in this case, there was no straightforward way to define the set of markets to be included (in the limit, this would be 100 per farmer). So we included, for each farmer, just three, the three markets which were pre-selected by the team as being the closest to the village. Results in Column (1) suggest that farmers tend to purchase at those markets which have more permanent agro-dealers present. Columns (3) and (4) present the split-sample results: farmers who purchase little urea on the left, and those that purchase more on the right. We can see that for the former, frequent visits tends to correlate with purchases.

The fact that farmers report differences in expected fertiliser quality between markets tells us that they do not believe the issues with quality to stem from upstream sources like wholesalers or the port, but rather their concerns are related to downstream factors including transportation, competition, or a lack of trust in dealers – a belief that there are dealers out there willing to cheat. Previous experience with fertiliser correlates with better beliefs about its quality, suggesting that experience can restore trust, at least to some degree (or that those who start out with better beliefs are more likely to use fertiliser). Overall, farmers appear to think in more positive terms of those markets which are larger, have less turnover, and are further away from their farm. Farmers who purchase substantial amounts of urea tend to purchase at these types of market hubs as well.

6 Analysis and Results

6.1 Effect on farmer beliefs

We start with the farmer-level analysis, and with our main variable of interest, farmer beliefs about fertiliser quality. Given the nature of our intervention, this is the main mechanism of a possible change in fertiliser use. Information collected in the in-person endline survey documents the importance, and strength, of our village information treatment. Almost everyone we interviewed in the treatment villages at endline in person had attended our informational meeting.

We define two dependent variables: the average (across markets) number of bad bags (out of ten) and the binary equivalent, whether or the farmer has any concern about fertiliser quality. We make use of the balanced panel of the in-person baseline survey with the endline phone survey. Recognizing balance in these dependent variables, and noting that autocorrelation is low in the beliefs data (around 10%), we follow McKenzie (2012) and proceed with an ANCOVA estimation. Subscript i refers to the farmer, subscript v refers to the village, *end* refers to the endline round (collected late 2019) and *base* refers to the baseline round (collected early 2019). Standard errors are clustered at the village level.

$$beliefs_{i,v,end} = \beta_0 + \beta_1 INFO_v + \beta_2 beliefs_{i,v,base} + \gamma X_{i,v,base} + \epsilon_{i,v} \tag{1}$$

Where $INFO$ refers to whether or not the village was selected as a treatment village, and $base/end$ refers to the base/endline data, respectively. Baseline control variables $X_{i,v}$ include baseline measures of sex, age, education, land owned, farm experience, risk aversion, number of household members and the number of markets visited. We test the hypothesis β_1=0.

Table 5 presents the results of specification (1). The effects reported are statistically significant and sizable. The intervention decreases the farmer's estimate of the number of bad quality bags by 0.6, which represents an effect size of 30%. Whether or not a farmer has any concerns also declines by 0.1, an effect size of 12%.

Figure 7 presents the distribution of the first dependent variable by round and by treatment status of the village. The top panel shows the baseline distributions, while the bottom panel shows the endline distributions. Once again, one notes balance across treatment groups at baseline. However, changes occur between base and endline in both groups, although more so in the treatment villages. Not all farmers in the treatment group were convinced by the information treatment however.[18]

We next use village-level panel in Appendix Table A.9 to test for village-level changes in beliefs. The dependent variables are the village-level mean (Column (1)) and the standard deviation (Column (2)) of the number of bad quality bags (out of ten). Column (3) presents the results for the ratio of these two variables. As the auto-correlation is low, and we want to account for the number of observations in each village in each round, we opted for a difference-in-difference estimation. Column (1) confirms the results in Table 5: the village treatment reduces the average of the number of bad bags (out of ten). Further inspection reveals that this is driven by villages which had over 80% of concerned farmers at baseline. It is in these villages that the treatment has resulted in fewer farmers being concerned; their concerns after the treatment are also less severe. The results in Columns (2) and (3) indicate that beliefs within villages are diverging, and not converging, due to the treatment. In effect, village disagreement appears more common after the treatment as while many change their minds, in each village, several farmers continue to hold on to their pessimistic beliefs.

One might be concerned about spillovers. We believe that between-village spillovers are limited, largely due to the geographic isolation of the villages. In our endline survey, farmers in the treatment villages reported that the information received in the village meeting was shared with non-participants, but almost entirely within the village. A more significant

[18]Further farmer-level analysis reveals that not all farmers alter their views favorably in either village type, although the average change in beliefs is comparable between farmers who purchased fertiliser before and those who did not.

concern is the effect of nearby market interventions on control villages. Recall that while our treatment was clustered in market-village units, villages might still be within a reasonable distance of other markets. We return to this point the last sub-section of the analysis. For now, we note that the effects estimated in this subsection should be viewed as a lower bound due to these potential spillovers.

6.2 Effect on farmer purchases

We investigate the effects of the village intervention on fertiliser purchase and use using a difference-in-difference specification (as the auto-correlation in urea use is high, around 60%). We have two measures: a binary measure captures whether the farmer purchased a particular fertiliser in the previous growing season, and a continuous measure captures the kilograms of each fertiliser purchased (where we set the non-users at zero).

$$use_{i,v,t} = \beta_0 + \beta_1 INFO_v * AFTER_t + \beta_2 INFO_v + \beta_3 AFTER_t + \gamma X_{i,v} + \epsilon_{i,v,t} \qquad (2)$$

Where use represents the binary or continuous measure $INFO_v$ refers to the village treatment and = 1 if the village was treated, and = 0 if the village was not treated. The variable AFTER refers to the data collection round and = 1 if this was the endline, collected in 2020 but referring to the 2019 main growing season, or = 0 if this was the baseline, collected in 2019 but referring to the 2018 main growing season. Baseline control variables $X_{i,v}$ include baseline measures of sex, age, education, land owned, farm experience, risk aversion, number of household members and the number of markets visited. Standard errors are clustered at the village level. We test the hypotheses $\beta_1 = 0$.

To test for effects of the treatment on fertiliser use per cultivated acre (which we only observe at endline in reference to the 2019 main growing season) we use:

$$use_{i,v} = \beta_0 + \beta_1 INFO_v + \gamma X_{i,v} + \epsilon_{i,v}, \qquad (3)$$

Where we we test the hypothesis: $\beta_1 = 0$.

In our interpretation, we treat fertiliser purchase quantities and fertiliser application quantities as equivalent. Baseline data established that farmers do not store fertiliser across seasons nor do they purchase fertiliser and resell to others.

Table 6 presents the effects of the village intervention on fertiliser purchases. The village treatment increases the likelihood that a farmer purchased urea fertiliser by 10 percentage points (a 27% effect size) in Column (2). The village treatment does not have a statistically significant impact on the amount of urea purchased (Column (1)). In Appendix Table A.10 we present the effects on the non-urea purchases. We do not observe any meaningful effects (there is a significant but economically small negative coefficient on ammonium sulfate fertiliser) suggesting the information treatment which focused on urea did not affect the beliefs of farmers regarding other fertiliser, or, more likely, that we are under powered to detect any such spillover effect, if present (see Table 3).

The discrepancy between Columns (1) and (2) in Table 6 suggests that new users might be driving the overall effect. To explore this point, we present the split-sample analysis. Columns (3) and (4) present the results for those farmers who had previously used fertiliser and Columns (5) and (6) presents the results for those farmers who had never used fertiliser before. We note a sizable statistically significant increase among the second group of farmers, both for the binary and the continuous measure. Farmers who had experience with fertilisers were more likely to purchase fertiliser but did not significantly increase the average amount they purchased.

Table 7 presents the effect on fertiliser use per acre using specification 3. A 5.6 kg per acre increase corresponds to an effect size of about 46%. We again note a discrepancy between (baseline) users and non-users, with a percentage-wise apparently more sizable response in the latter group (although this difference is not statistically significant).

6.3 Effects on farmer inputs and outputs

In this subsection we document effects on other farmer investment or outcome variables. The regressions in this section are based on a much smaller sample, using endline data from the in-person survey.[19] As many of these variables were not recorded at baseline, we use a specification similar to 3 in Table 8. Column (1) considers effects on cultivted maize acreage, Columns (2) and (3) on use of agro-chemicals and hybrid seeds and Column (4) presents maize yield effects.

The results suggest that treated farmers are more likely to use hybrid maize (this effect is substantial in magnitude and almost statistically significant), but not more likely to expand maize acreage or use more agro-chemicals. Farmers may be exploiting the well-known production complementarities between hybrid seeds and fertiliser use (Abay et al., 2018; Sheahan and Barrett, 2017). But alternative explanations are also plausible. Farmers' increased trust in their local agro-dealers might translate into more trust in the quality of the hybrid seeds (as suggested by Ariga et al. (2019*b*)). Or perhaps some farmers decided to purchase improved seeds while they were purchasing fertiliser, having already incurred the transportation cost to the shop.

We note no statistically significant effects on maize yields. This was to be expected. Effects on yield take time, and are difficult to detect in this smaller sample. In addition, fertiliser could also have been used on other crops than maize, as suggested by the baseline data.

6.4 Effect on agro-dealer prices, sales and WTP

A market-level response to the market intervention could consist of either a response in quantities sold or a response in prices or, possibly, both. As fertiliser prices are controlled

[19] With a smaller sample, both balance and attrition become more of an issue. In terms of balance, risk aversion now appears to be comparable across treatment and control villages. But, importantly, the control villages within this sample start off with significantly worse beliefs in terms of fertiliser quality; and this being the main channel of treatment effect, might imply that, to some extent, we might be under-estimating the village treatment effect. Attrition is also significant, at 27% despite the fact that we visited the villages in person. This is partially due to the fact that one village was not reached at all. Attrition appears not correlated with the village treatment status. See Appendix Table A.1.

by the government with agro-dealers concerned about enforcement, our hypothesis was that the effect on prices would be limited.

We hence start this section by considering a possible effect on prices using specification 4 (recognising we have endline data only). We restrict our sample to the balanced panel, i.e. those agro dealers for whom we have both base and endline data. We also use this specification to consider the effects on the WTP for fertiliser certification, another variable which was only available at endline.

$$price_{j,m} = \beta_0 + \beta_1 INFO_m + \gamma X_{j,m} + \epsilon_{j,m} \tag{4}$$

Where $INFO_m$ refers to the market treatment and = 1 if the market was treated, and = 0 if the market was not treated. We test the hypotheses $\beta_1 = 0$. The control variables $X_{j,m}$ include the sex, age and education level of the owner, the number of years the business has been selling fertiliser, the total capacity of the business, the asset index for owned assets, and whether or not the business has an TFRA license and is an CNFA member. Errors are clustered at the market level.

Table 9 presents the results. In Column (1), we note no statistical significant impact on the price of urea sold (note that the sample is further restricted to those businesses which reported prices). This is consistent with the fact that prices are regulated by the government. However, the effect estimate lacks precision. We repeat this exercise using the farmer-reported prices (at endline). Appendix table A.11 reports the result. The dependent variable is the prices farmers report paying per kg at endline. Note that samples are small and vary across the columns because the data are only known conditional on the farmer having purchased the fertiliser. Again we note no statistically significant effects on these prices paid.

In Column (2) of Table 9 we note a significant effect on the WTP. To interpret the significance of this effect, one should keep in mind that several dealers noted they would not be willing to pay anything for such a scheme. These sellers indicated that they were not the decision-maker or that it's the government who should guarantee the quality of fertilisers. Despite the inclusion of these zero offers, we note a sizable coefficient, 35,349 TZS, representing an effect size of about 70 percent (although the p-value is 0.2, and hence not statistically significant). It is notable that even among the control group, those who were not exposed to the market treatment, the WTP is substantial, with an average WTP of about 20 USD.

To investigate the effects on sales, we alter our specification, taking advantage of the panel data. Denote the agro-dealer by subscript j, the market by m, and the round by t. We use a difference-in-difference specification 5:[20] [21]

$$sales_{j,m,t} = \beta_0 + \beta_1 INFO_m * AFTER_t + \beta_2 INFO_m + \beta_3 AFTER_t + \gamma X_{j,m} + \epsilon_{j,m,t} \quad (5)$$

Where sales represents a range of binary and continuous measures, including whether the dealer had ever sold urea, had urea in stock at the time of the survey, the amount of urea sold that calendar year and the total amount of all fertiliser sold that calendar year. $INFO_m$ refers to the market treatment and = 1 if the market was treated, and = 0 if the market was not treated. The variable AFTER refers to the data collection round and = 1 if this was the endline, collected in 2020 but referring to the 2019 year, or = 0 if this was the baseline, collected in 2019 but referring to the 2018 year. We test the hypotheses $\beta_1 = 0$. The control variables $X_{j,m}$ include the sex, age and education level of the owner, the number of years the business has been selling fertiliser, the total capacity of the business, the asset index (owned assets), and whether or not the business has an TFRA license and is an CNFA member. Standard errors are clustered at the market level.

Table 10 presents the results of Specification5. Columns (1) through (3) again refer to

[20] The auto-correlation in the continuous dependent variables is high, ranging from 0.4 to 0.6 in these samples. Hence, following (McKenzie, 2012) we opt for a difference-in-difference specification instead of an ANCOVA.

[21] See also Hossain et al. (2019), Arouna et al. (2021), Fernando (2021), and Cole and Fernando (2021), who opt for a difference-in-differences over ANCOVA in these circumstances.

the balanced sample, while columns (4) and (5) trim the sample further to include only those agro-dealers who sold fertilisers in both periods. We detect no statistically significant effects of the treatment on the extensive margin: either the likelihood of having urea currently in stock or selling urea in a given year. Nor do we note any statistically significant effects in the internal margin, on sales of urea or fertilisers as a whole.

One of the reasons of these lack of effects might be that sales is not normally distributed, but tends to have a long right-tail. In Appendix Figure A.3 we plot the kernel density of the quantity of urea sold in 2019 (capped at 50,000 kg/year). The treatment group distribution has a significantly longer tail than the control group, indicative of possible effects among a sub-set of agro-dealers. The presence of fat tails can lead to an under powered study as well as overstated effect sizes using a standard, frequentist approach (see, among others, (Fernández and Steel, 1998), (Kruschke, 2013) and (Gelman and Carlin, 2014). For an introduction, see (Rubin, 2005)).

Hence, we also present the estimation results of an alternative model, a Bayesian hierarchical model. We use the R-package developed by Meredith and Kruschke (2021) (including their conservative priors which are close to zero) and rely heavily on the presentation of Tushi and Vasilaky (2023) to estimate the average treatment effects of the market treatment on the various sales variables. In Table 11 we present the results of 100,000 draws from the posterior distribution of the average treatment effect. We focus our discussion on rows (4) through (6), which present the continuous variables. We note sizable impacts on the quantity of urea sold, an effect size of almost 5%. The probability that the true value is greater than zero is 90%. The impact remains sizable when consider the smaller sample of agro-dealers who sold fertilisers in both periods, with an estimated effect sizes of 5% of the total fertiliser sales.

We conclude this section with a reference to an additional data source we have so far not used. We collected weekly sales data via the phone during the 2019 growing season (between base and endline).[22] These data include: the number of customers, sales of urea, NPK and DAP; price in the market of urea, NPK and DAP (in kg). Note that prices are a sensitive topic, and hence we only inquired about the "going rate in the market", attempting to make this question less personal. We collected these data primarily for ethical reasons, to ensure that we would catch any negative impacts of our treatment in a timely fashion were they to occur. The strength of these weekly data lies in the frequency, but as the unit of measurement differs (we elicited prices per kg rather than per 50 kg), an additional source of discrepancy may have been introduced.[23] In addition, there is significant attrition: only 70 dealers provided information for each week and we note significant sample selection: dealers in the control group are selling more than dealers in the treatment group at the start of our weekly recordings; in addition not all information was used as some observations had missing weeks or price information).

Keeping these limitations in mind, in Appendix Table A.12 and Appendix Table A.13 we present the results of a series of dealer fixed effects regressions. We focus on the interaction effects between the weeks and the treatment (assuming that any treatment effect might be gradually revealed in the data): How sales and pricing change as the weeks progress in the two groups. We again note a null effect on prices (barring a small effect on DAP), and a positive correlation with the number of customers purchasing fertilisers. We do not note any effects on sales; the large variance likely plays a role in our inability to detect any movement in sales.

6.5 Changes in farmer beliefs and purchases across markets

In this section we present the analysis at a market-level. We elicited farmers' beliefs at this level allowing for between-market comparisons. In the village intervention, information was provided on the nearest treatment market. Hence, as no experimental between-market

[22] Agro-dealers received 5000 TZ (equivalent to 2 USD) per call.

[23] While most dealers sell in kg, and when it comes to weekly data, this is the relevant unit, it is also the case that selling in small dealer-packaged units was not allowed at the time of the data collection. This more accurately reflects the amounts the farmers purchase but might introduce another source of measurement error related to the ban on sales of small bags which was introduced in the year of our study.

variation was introduced by us, the results in this section should be interpreted as correlations - correlations between beliefs changes in the treatment villages and characteristics of these markets as they relate to the farmers.

In Appendix table A.14 we map beliefs (measured as number of bags with bad quality fertiliser - out of ten) on measures of market characteristics (market size, market distance, market churning) in Column (1), adding the farmers' baseline relationship to these markets in Column (2) (whether the farmer had visited the market at baseline), and Column (3) (whether the farmer had purchased at the market at baseline). This regression controls for farmer fixed effects (and as such also the village intervention variable). The coefficients presented in this table are the interaction coefficients with this village intervention variable. We use the balanced farmer panel - limited to those observations for which we have market-level beliefs at both base and endline. Column (3) is further conditional on the farmer having purchased fertiliser at baseline, hence the smaller sample.

We do not see any evidence that beliefs change differentially for larger markets. Beliefs do appear to respond more strongly in response to the information treatment for markets located further away (which we know from the baseline analysis tend to be the larger markets as well). Nor do we find evidence that farmers change their beliefs more for markets where they lack prior experience.

We continue to use the farmer/market level panel to gain an understanding as to whether farmers might change the location of their visits and purchases as a response to the treatment. We use an ANCOVA specification with a dependent variable baseline control (with additional farmer-level baseline control variables). We opt for ANCOVA rather than a farmer-fixed effects specification, as the variables are not entirely comparable across the two rounds and measurement error is expected to be substantial, and possibly, differential between rounds.[24]

[24] At baseline, we asked the farmer to list all markets visited. During the in-person endline survey, we proposed the three pre-selected markets, and allowed farmers to add more to this list. In addition, while the baseline referred to the past 12 months, the endline-in-person analysis only covered the previous long rain season. During the phone endline survey, the enumerators mistakenly only asked for one possible market per fertiliser type purchased, possibly resulting in an underestimate. Another limitation for both purchasing and visit data is that farmers were allowed to mention markets by name. While our census of markets was

Appendix Table A.15 presents the results. Columns (1) and (2) use the in-person endline data to establish the village intervention effects on market visits. While the sample is small, we note no statistically significant impact on either the number of markets visited, nor on whether the local, associated market was visited. As markets are visited for many reasons, this was not a margin where we expected any effects. Columns (3) and (4) use the phone endline data to establish the correlations between the village intervention and market purchasing behavior. The dependent variable in Column (3) is the distance travelled to purchase fertiliser (in km), the dependent variable in Column (4) is whether the farmer purchased fertiliser at the local, associated, market. The sample is limited to those farmers who purchased fertiliser before. Hence, the results presented in these columns should be viewed as suggestive correlations only. We find that conditional on purchasing fertiliser, farmers are more likely to use closer markets (the effect size is over 50% on distance, and almost statistically significant in Column (4)). This should be seen against a backdrop of on overall move towards purchasing in larger markets, which tend to be further away. As the information treatment centred around the associated market, which was the nearest market, this implies that our treatment may have helped build some trust in these local markets.

7 Conclusion

The functioning of rural markets is critical to economic growth and agricultural development. In most of Sub-Saharan Africa, agro-dealers operate in largely unregulated environments with few geographically proximate competitors. Consumers and policy-makers alike often suspect that these conditions give rise to high mark-ups and low quality. Could local monopolies extract economic surplus from a uncoordinated population of poor farmers? Recent evidence is mixed, at least on pricing. Bergquist and Dinerstein (2020) use a randomized controlled trial with maize traders in Kenya to show evidence of significant mark-ups, while Dillon and Dambro (2017) conclude that there is little evidence of non-competitive behavior

expected to limit the cases where we had no market ID, in practise there were a significant number of markets where we could not assign any ID. These markets are dropped in the analysis as well.

in their survey of the literature on output markets in Sub-Saharan Africa.

Work by Michelson et al. (2021), Hoel et al. (2021), and Bold et al. (2017) establish widespread suspicions among farmers about urea fertiliser quality in Sub-Saharan Africa. The concerns are considerable in their scope and severity and appear to affect farmer demand in experimental settings. On average across these studies, farmers expect that one out of every three bags of urea in their local market is of bad quality. Hoel et al. (2021) and Michelson et al. (2021) show in experimental settings that Tanzanian farmers are willing to pay less for urea of unverified quality, but that they respond and revise their willingness-to-pay in response to information that guarantees the good quality of the fertiliser.

We implemented a randomized controlled trial in 100 markets and 148 villages in Tanzania to test the effects of an information campaign about urea fertiliser quality. We distributed pamphlets and posters in randomly selected markets and villages, with the message that all urea tested in a study we ran in 2016 (Michelson et al., 2021) was found to be good.

Concerned farmers are present in all villages, with the fraction of farmers concerned around seven out of ten. Prior fertiliser use appears to be a key correlate of trust in product quality: farmers who used fertiliser before report significantly fewer concerns.

The information treatment significantly improved farmer beliefs about fertiliser quality six months after the intervention. Treatment also increased urea usage at the extensive margin, but not the intensive margin, suggesting that the primary effect of distrust in these communities may have been dissuading many farmers from using commercial fertiliser altogether. The intervention, which centred around urea, the most commonly used fertiliser, did not spill over to other fertilisers. While farmers increased their use of urea, they did not increase their use of DAP, CAN, NPK, or SA.

At the dealer level, we find a significant increase in the amount of urea fertiliser sold in treatment markets (when using a model which takes into account the fat-tailed data) – an effect size of nearly 5%. We find no effect on the price.

These represent sizable effects for a relatively low-touch information campaign. Other studies in which farmers are provided with information often produce disappointing results. Providing farmers with information about a new crop insurance product does not result in much uptake (Jensen, Barrett and Mude, 2016). Informing farmers about their soils nutrient limitations does not increase use of appropriate fertilisers either (Harou et al., 2022). The expected effects depend on whether or information is the primary constraint. Hsu (2020), for example, provide information on maize seed market in Kenya where these concerns are considerable and substantiated. [25]

Despite these large effects, one should keep in mind that the the lack of trust in fertiliser quality is one of many constraints that farmers face in this region. Other constraints include insufficient access to credit to finance production (Boucher, Carter and Guirkinger, 2008) and post-harvest storage (Cardell and Michelson, 2023; Burke, Bergquist and Miguel, 2019), uninsured production risk (Karlan et al., 2014; Dercon and Christiaensen, 2011; Carter and Barrett, 2013), lack of market access and output market price volatility (Minten, Koru and Stifel, 2013; Croppenstedt, Demeke and Meschi, 2003), inconsistent time preferences (Duflo, Kremer and Robinson, 2011), lack of knowledge on the soil's nutrient limitations (Harou et al., 2022; Corral et al., 2020). Spatial heterogeneity in agronomic conditions and therefore returns to fertiliser are also relevant. Sheahan and Barrett (2017) find large spatial heterogeneity in fertiliser usage among farmers in sub-Saharan Africa and Chamberlin, Jayne and Snapp (2021) document important spatial variation in farm gate crop/fertiliser price ratios and in environmental factors including rainfall. Hence, lack of trust in fertiliser quality is unlikely to be the primary constraint to fertiliser adoption and use, but it may contribute to and exacerbate the effects of other constraints.

The way we implemented our intervention likely contributed to its success. The infor-

[25] Limited effects are document after providing information on migration possibilities Tjaden and Dunsch (2021), returns to education Jensen (2010), the benefits of smoke-free cooking and of cleaning drinking water Bonan, Kazianga and Mendola (2020); Bennear et al. (2013)), HIV/AIDS tests Thornton (2012), food safety at local food stalls Daniele, Mookerjee and Tommasi (2021)), Nyqvist, Svensson and Yanagizawa-Drott (2020)), restaurant hygiene Jin and Leslie (2009)). An exception is (Annan, 2022), who assesses the impacts of an information intervention revealing seller's fraud regarding mobile money payments and documents a significant impact on both sellers and buyers. Sizable effects are also reported by Bai (2018) who considers the impact on sellers from a certification scheme for watermelons in China.

mation intervention was led by a trustworthy party, a local public research university. We also provided the information treatment to the entire village. This treatment of the entire village avoided some of the pitfalls with social learning in which disconnected individuals do not receive the information first-hand (as Eyster and Rabin (2014); BenYishay and Mobarak (2019); Maertens (2017)). Finally, fertiliser is a product in a context in which quality beliefs are not tangled up with political or other aspects of one's identity Zimmermann (2020). As such, belief stickiness, i.e., a situation in which beliefs do not respond adequately to new information presented (as in as in Falk and Zimmerman 2018), should be limited when being confronted with credible information from our research team.

We conclude on a more speculative note. While we had set up our study as a standard randomized controlled trial, our overall goal was to use the research to provide insight into how farmers form and change their beliefs about an important production input. Understanding where the break-down of trust occurs is important as determines not just the impact of our information treatment but also the other relevant policy options. Do farmers believe the quality of all inputs is poor due to upstream issues, due to corruption, delays and mishandling at the port? Or do they believe the issues are at the market level? For example, transportation to far-away markets might be problematic on poorly maintained roads in a hot climate. Or, do farmers believe the quality at specific shops is poor due to adulteration of the product, or other actions taken, by opportunistic dealers?

Our market-level results suggest that the latter two factors are more important than the first. Farmers' concerns vary substantially by market, with farmers expressing fewer concerns for larger markets. These larger markets, which tend to be further away from the homestead, tend to be the markets where most farmers purchase fertilisers (as opposed to the smaller markers near one's village that farmers often visit for other, more routine transactions). This tells us that farmers do not believe the issues with quality stem from upstream sources, like wholesalers or the port. Fertiliser quality concerns vary across markets, which suggests market-level issues regarding transportation, competition, or a spatially-varying lack of trust in dealers. Conditional on the location, the market structure matters – larger markets with more market churn are more trusted and farmer beliefs about smaller markets are more likely to respond to the information provided, indicating that the lack of trust in dealers' actions is significant. As previous experience with fertiliser correlates with better beliefs about its quality, it may be that some degree of experience can restore trust to some degree (or that those who start out with better beliefs are more likely to use fertiliser). The information intervention too restores some of this trust, although not completely, as still a sizable number of farmers in the treatment village have remaining concerns at endline.

Nevertheless, our promising results show that changing beliefs is an important first step in changing behavior.

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Figures and Tables

Figure 1: Study intervention timeline (December 2018 – January 2019)

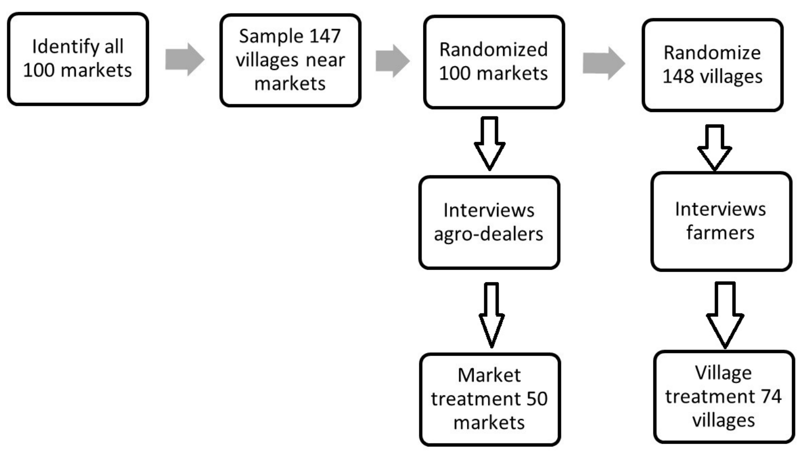
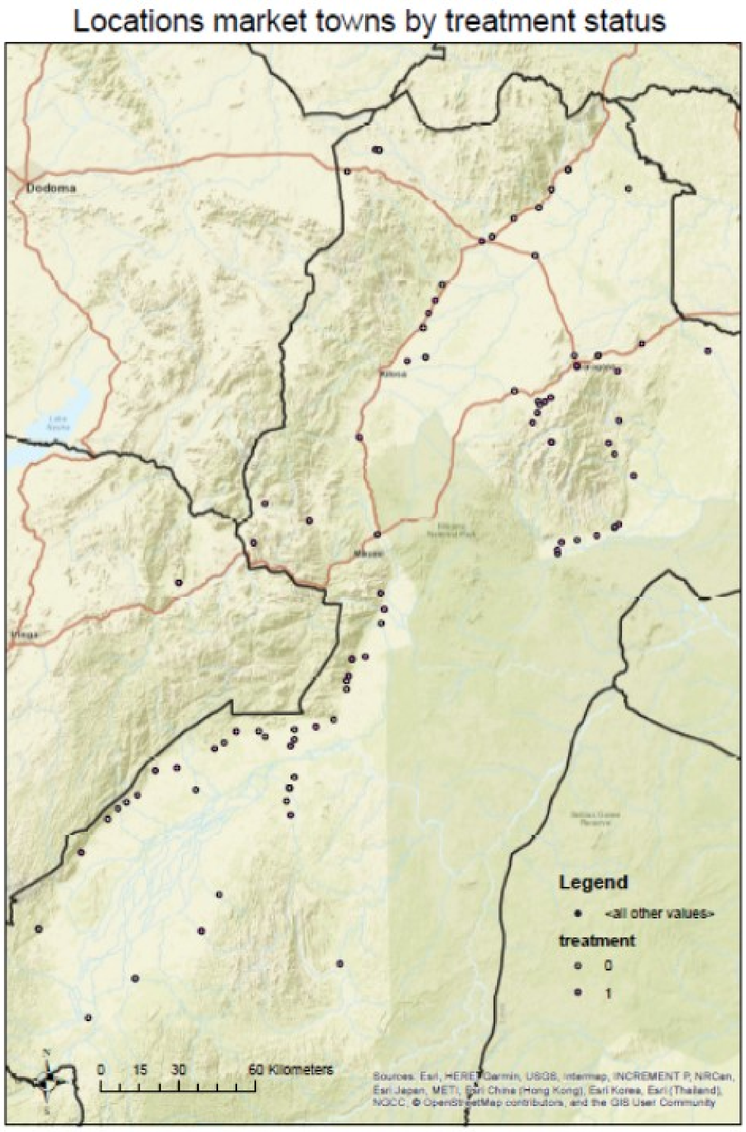
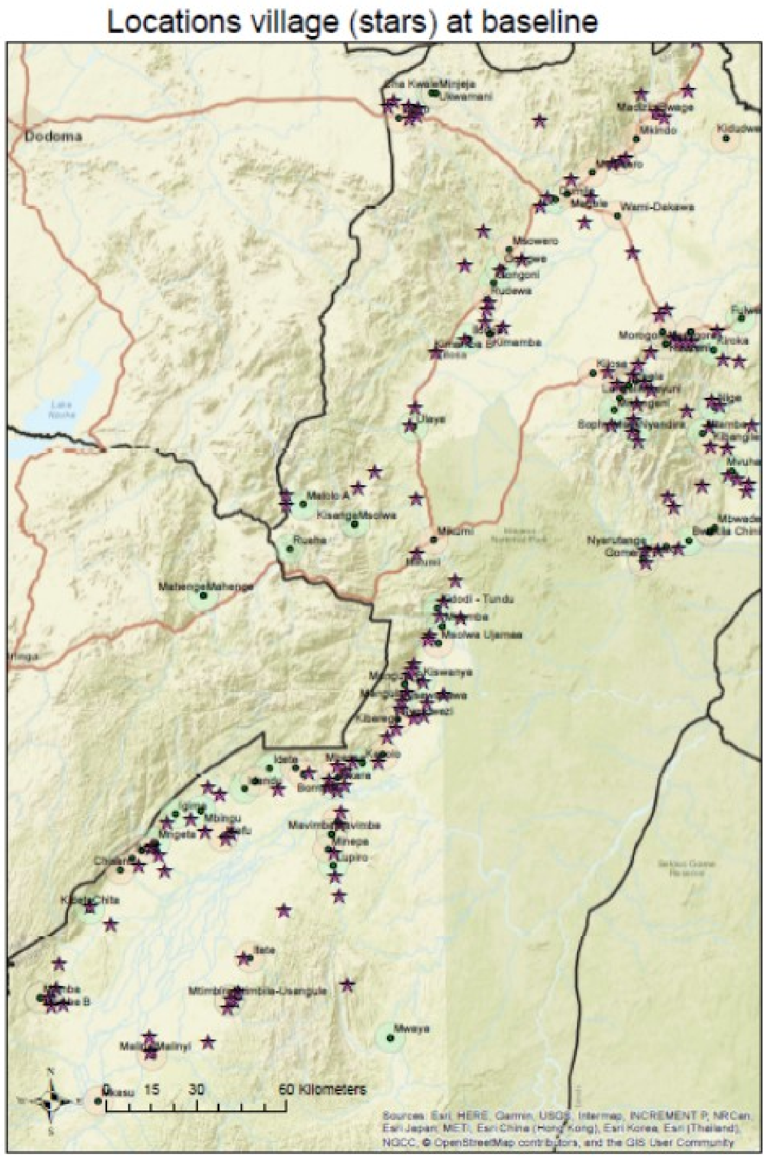


Figure 2: Study area map



Note: Markets are indicated with dots. Blue dots are control markets and purple dots are treatment markets. The red lines indicate roads, the blue waterways and the black region boundaries.

Figure 3: Study area map - village locations (stars)



Note: Villages are indicated with stars. Dots are the markets. The red lines indicate roads, the blue waterways and the black region boundaries.

Figure 4: Data collection

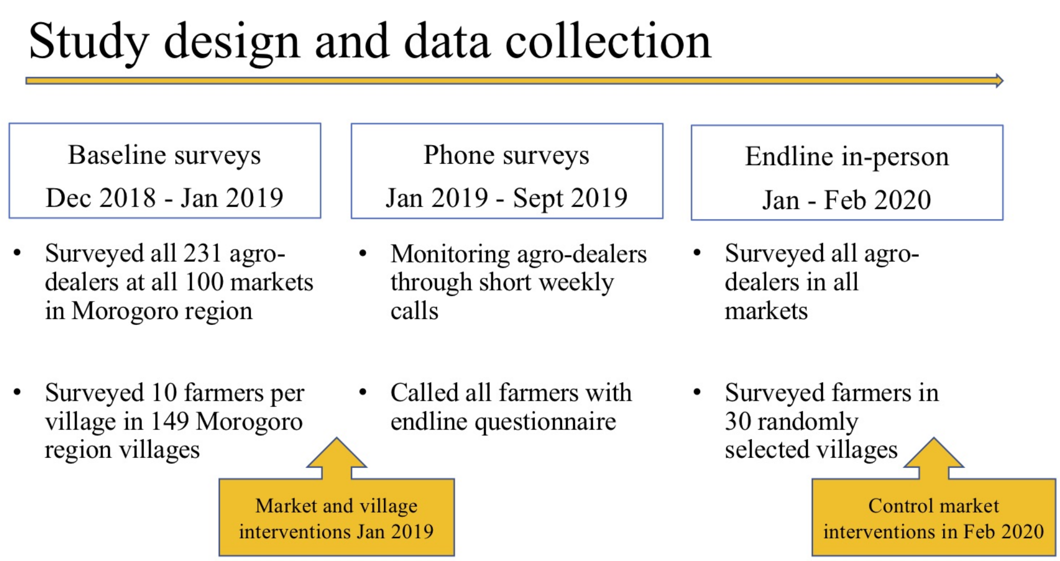


Figure 5: Kg fertiliser per acre cultivated, conditional on having purchased fertiliser, at baseline (balanced panel)

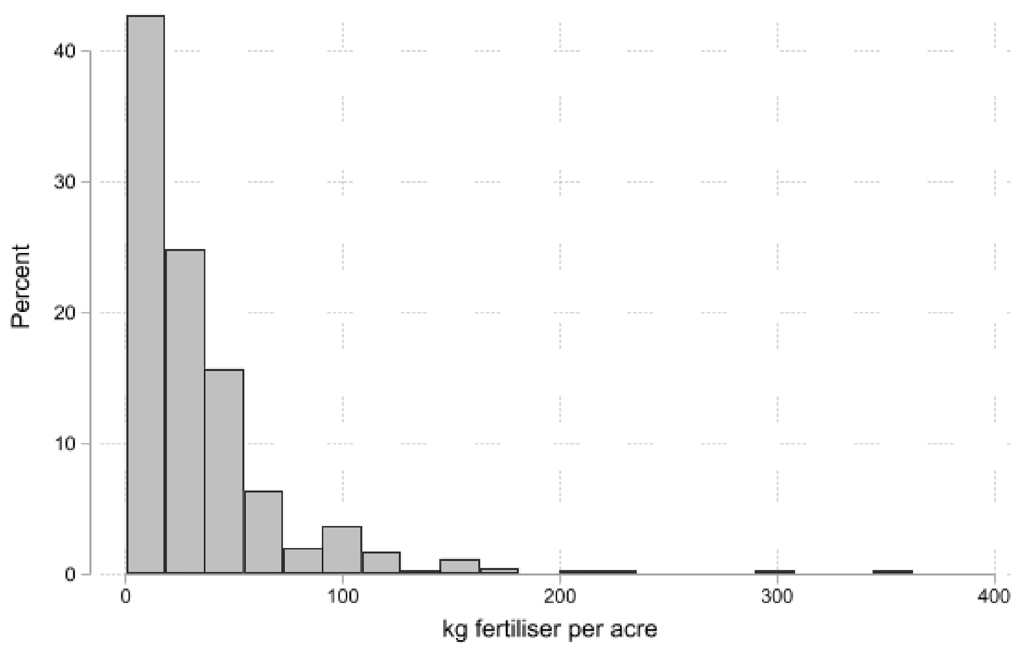


Figure 6: Distribution of the beliefs regarding fertilizer quality at baseline, in bad quality bags out of ten (balanced panel)

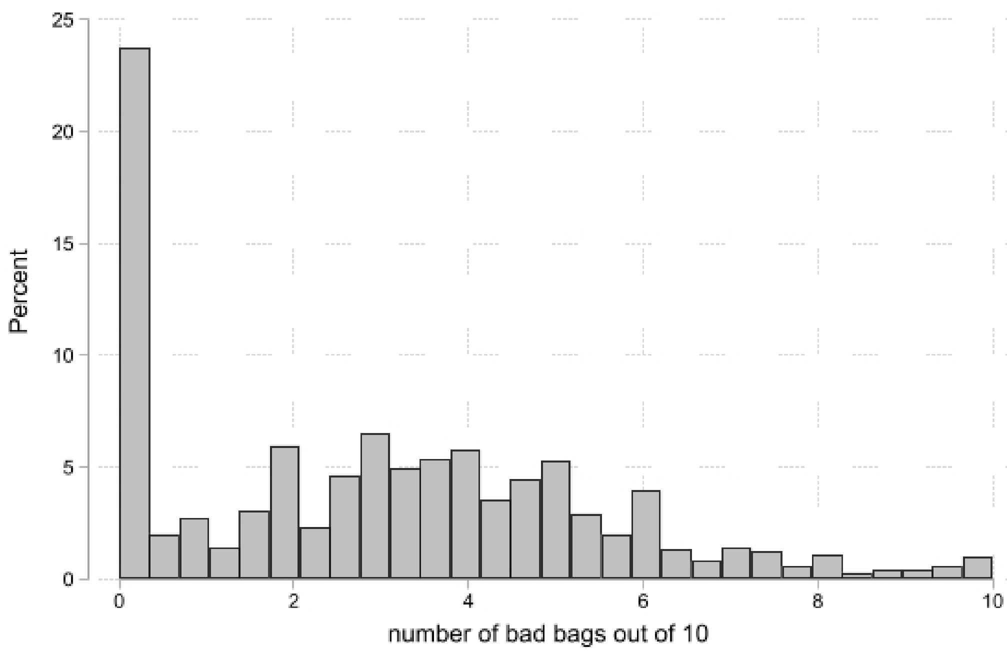


Figure 7: Histogram of beliefs regarding fertilizer quality (average number of bad quality bags out of ten), by round and by village treatment

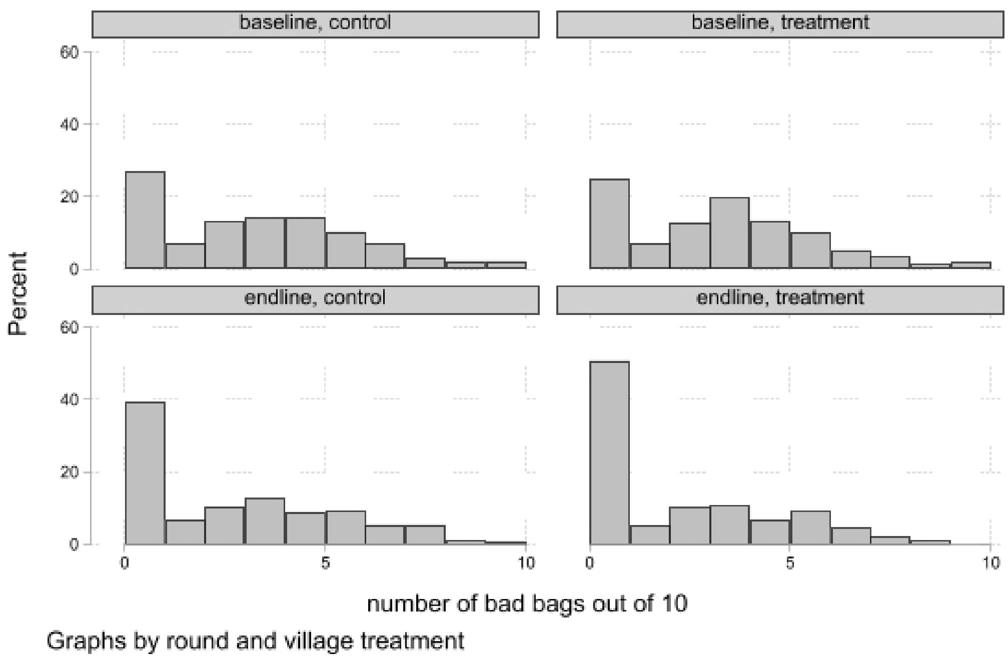


Table 1: Public opinions on corruption in Tanzania

Category	Population	Farmers
Trust in government institutions		
Trust the President just a little or not at all	26.42%	21.22%
Trust Parliament just a little or not at all	31.75%	27.65%
Trust their local government council just a little or not at all	32.12%	28.62%
Think most or all of the President and Officials in his Office are involved in corruption	4.71%	4.18%
Think most or all of Parliament is involved in corruption	7.50%	7.23%
Think most or all of their local government councilors are involved in corruption	9.21%	8.68%
General trust in people		
Think that corruption increased somewhat over the past year	10.88%	10.37%
Think that ordinary people cannot make a difference in the fight against corruption	43.50%	46.70%
Think that ordinary people risk retaliation or other negative consequences if they speak against corruption	70.54%	69.45%
List corruption in their top three most important problems that the government should address	5.33%	4.18%
Personalized trust in people		
Never sure that vendors sell the correct amount of a kg of maize or rice to them	45.08%	45.74%

Note: Based on Afrobarometer Round 7 Data for Tanzania (2018) Farmers = Respondents who reported their main or last occupation being in agriculture, farming, fishing, or forestry.

Table 2: Number of agro-dealers interviewed at base and endline

	Baseline category	
Endline category	Interviewed at baseline	Not interviewed at baseline
Interviewed at endline	232	132
Not interviewed at endline	66	NA

Table 3: Descriptive statistics farmers at baseline (analysis sample)

Variable	(1) All villages	(2) Control Villages	(3) Treatment villages	(4) p-value
Sex (0 = male)	0.40 (0.49)	0.42 (0.49)	0.38 (0.49)	0.19
Age (years)	45.24 (12.14)	44.68 (12.17)	45.80 (12.09)	0.15
Household members	5.55 (2.58)	5.53 (2.47)	5.58 (2.68)	0.76
Land owned (acres)	6.86 (9.36)	7.29 (10.72)	6.43 (7.77)	0.15
Farm experience (years)*	16.09 (11.53)	15.70 (11.34)	16.49 (11.71)	0.28
Risk loving**	3.18 (1.52)	3.07 (1.52)	3.29 (1.52)	0.02***
Ever purchased fertiliser (1 = yes ; 0 = no)	0.59 (0.49)	0.58 (0.49)	0.61 (0.49)	0.35
Fertiliser purchased in last growing season (1 = yes ; 0 = no)	0.40 (0.49)	0.38 (0.48)	0.43 (0.49)	0.08*
Urea purchased in last growing season (1 = yes ; 0 = no)	0.37 (0.48)	0.35 (0.47)	0.40 (0.49)	0.16
Amount of Urea purchased (kg) last growing season	41.68 (146.14)	41.34 (174.13)	42.02 (111.59)	0.94
NPK purchased in last growing season (1 = yes ; 0 = no)	0.02 (0.14)	0.02 (0.14)	0.01 (0.14)	0.99
Amount of NPK purchased (kg) last growing season	1.78 (25.72)	1.06 (9.49)	2.45 (35.10)	0.38
DAP purchased in last growing season (1 = yes ; 0 = no)	0.12 (0.33)	0.12 (0.33)	0.12 (0.33)	0.78
Amount of DAP purchased (kg) last growing season	9.70 (70.71)	11.58 (86.48)	7.84 (50.30)	0.40
CAN purchased in last growing seasons (1 = yes ; 0 = no)	0.06 (0.24)	0.05 (0.21)	0.08 (0.27)	0.02***
Amount of CAN purchased (kg) last growing season	4.58 (37.72)	2.65 (14.68)	6.51 (51.22)	0.10*
Number of markets visited in past 12 months	1.36 (0.96)	1.34 (0.96)	1.39 (0.96)	0.36
Number of markets purchased***	1.14 (0.39)	1.16 (0.44)	1.12 (0.35)	0.27
Number of bad quality bags of fertiliser (out of ten)	2.02 (2.30)	2.03 (2.34)	2.08 (2.27)	0.86
Share of farmers with any concern about fertiliser quality	0.77 (0.41)	0.77 (0.42)	0.78 (0.41)	0.49

Note: This table presents the results of a baseline balance test. Column (1) presents the average and standard deviation of the full analysis sample. Column (2) of the control villages, Column (3) of the treatment villages. Column (4) presents the results of a t-test with unequal variances testing the differences between the treatment and control groups. The sample contains all farmers who were present at both baseline in person interview, and endline call interview. N = 995 (control = 497; treatment = 498). *experience refers to the number of years the farmer has cultivated at this location. ** risk loving refers to the categorical answer to the question ‘compared to others, how much risk do you take’. Answers are coded from 1 = much fewer, to 5 = much more.*** The number of markets where purchased refers to the number of markets the farmer purchased fertiliser from in the the last growing season and is conditional on purchasing fertiliser that season.

Table 4: Descriptive statistics agro-dealers at baseline (analysis sample)

Variable	(1) All markets	(2) Control markets	(3) Treatment markets	(4) p-value
Sex owner (1 = female; 0 = male)	0.26 (0.44)	0.27 (0.44)	0.26 (0.44)	0.91
Age owner	42.72 (12.20)	43.34 (11.73)	42.41 (12.48)	0.58
Education owner*	2.20 (1.74)	2.35 (1.66)	2.12 (1.79)	0.32
TFRA fertilizer selling license (1 = yes ; 0 = no)	0.5 (0.5)	0.46 (0.50)	0.52 (0.50)	0.41
Tagmark member (1 = yes ; 0 = no)	0.38 (0.49)	0.37 (0.48)	0.39 (0.48)	0.75
Asset index**	2.82 (1.39)	2.80 (1.41)	2.83 (1.37)	0.88
Years selling fertilizer	4.17 (4.56)	4.55 (4.96)	3.95 (4.33)	0.36
Selling fertilizer every month (1 = yes ; 0 = no)	0.60 (0.49)	0.53 (0.50)	0.63 (0.48)	0.26
Number of customers present during interview	2.78 (3.79)	2.40 (3.18)	3.00 (4.08)	0.23
Ever sold urea (1 = yes ; 0 = no)	0.68 (0.50)	0.66 (0.48)	0.69 (0.46)	0.59
Quantity urea sold in 2019 (kg)	11,469 (26,638)	12,050 (27,501)	11,264 (26,421)	0.85
Ever sold NPK (1 = yes; 0 = no)	0.42 (0.49)	0.39 (0.49)	0.43 (0.50)	0.61
Quantity NPK sold in 2019 (kg)	5,407 (11,548)	4,748 (8,558)	5,710 (12,742)	0.67
Ever sold DAP (1 = yes; 0 = no)	0.51 (0.50)	0.50 (0.50)	0.52 (0.50)	0.70
Quantity DAP sold in 2019 (kg)	5,251 (14,030)	4,907 (10,255)	5,429 (15,697)	0.83
Ever sold Minjingu (1 = yes ; 0 = no)	0.05 (0.22)	0.01 (0.11)	0.07 (0.26)	0.01***
Quantity Minjingu sold in 2019 (kg)	3,937 (5,203)	NA	NA	NA
Ever sold CAN (1 = yes ; 0 = no)	0.60 (0.49)	0.60 (0.49)	0.60 (0.49)	0.89
Quantity CAN sold in 2019 (kg)	4,773 (12,874)	2,626 (4,736)	5,933 (15,506)	0.06*
Ever sold SA (1 = yes ; 0 = no)	0.40 (0.49)	0.33 (0.47)	0.44 (0.49)	0.08*
Quantity SA sold in 2019 (kg)	3,091 (9,904)	1,544 (4,967)	3,705 (11,258)	0.21
Total amount of fertilizer sold in 2019 (kg)	17,681 (55,649)	14,219 (36,367)	19,573 (63,811)	0.41
Urea currently in stock (1 = yes ; 0 = no)	0.48 (0.50)	0.48 (0.50)	0.48 (0.50)	0.91
Total current stock of fertilizer (kg)	6,394 (49,505)	17,232 (85,411)	1,023 (2,680)	0.16
Total current capacity to store fertilizer (kg)	17,082 (60,699)	16,301 (45,923)	17,408 (67,333)	0.90

Note: This table presents the results of a baseline balance test. Columns (1), (2) and (3), respectively, present the average and standard deviation of the full analysis sample, the control markets and the treatment markets. Column (4) presents the results of a t-test with unequal variances testing the differences between the treatment and control groups. The sample contains all agro-dealers who were present at both baseline and endline interviews. N = 232 (control = 82 ; treatment = 150). *(0 = primary; 1 = secondary ; 2 = trade school ; 3 = diploma ; 4 = BA and related ; 5 = Ms and related ; 6 = PhD). **The asset index is the sum of ownership of the following assets: mobile phone, smart phone, computer, pickup truck, motor bike, car and generator. The sales amounts of the individual fertilizer types are conditional on any sales in the past. The total stock and capacity were not computed for those firms that did not sell fertilisers at baseline.

Table 5: The effects of the village intervention on fertiliser beliefs of farmers

Variable	(1) Number of bad quality bags (out of ten)	(2) Farmer has concern about quality (1 = yes ; 0 = no)
Village intervention	-0.595***	-0.105**
	(0.198)	(0.0405)
Baseline dep. var.	0.102***	0.103**
	(0.0325)	(0.0403)
Baseline controls	Yes	Yes
Observations	953	953
R-squared	0.036	0.033

Note: This table presents the results of an OLS regression following an ANCOVA specification using the analysis sample (balanced panel between base and phone endline survey). The dependent variables are the average number of bags with bad quality (out of ten) in Column (1) and whether or not the farmer has any concerns in Column (2). Control variables include baseline measures of sex, age, education, land owned, farm experience, risk aversion, number of household members and number of markets visited. Errors are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.01$.

Table 6: The effects of the village intervention on fertiliser purchases of farmers

Variable	(1) Full sample Urea (kg)	(2) Full sample Urea (0/1)	(3) Fertiliser users Urea (kg)	(4) Fertiliser users Urea (0/1)	(5) Fertiliser non-users Urea (kg)	(6) Fertiliser non-users Urea (0/1)
Village intervention * After	8.532	0.106***	11.03	0.127**	6.120*	0.0884**
	(8.239)	(0.0333)	(13.26)	(0.0526)	(3.241)	(0.0348)
After	-9.158	-0.0512**	-17.83*	-0.137***	2.922**	0.0686***
	(5.694)	(0.0258)	(9.561)	(0.0433)	(1.274)	(0.0193)
Village intervention	4.063	0.0382	7.672	0.0340	0.454	0.00778
	(10.97)	(0.0476)	(15.87)	(0.0544)	(0.449)	(0.00536)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,956	1,956	1,166	1,166	790	790
R-squared	0.096	0.121	0.123	0.086	0.050	0.100

Note: This table presents the results of an OLS regression following a difference-in-difference specification. The dependent variables are a binary measure capturing whether the farmer purchased urea in the previous growing season, and the amount of urea purchased (kg) in the previous growing season. Control variables include baseline measures of sex, age, education, land owned, farm experience, risk aversion, number of household members and number of markets visited. Columns (1) and (2) present the results of the analysis sample (balanced panel between base and phone endline survey); Columns (3) and (4) present the results for those farmers who used fertiliser before and Columns (5) and (6) presents the results for those farmers who have not used fertiliser before. Errors are clustered at the village level. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$.

Table 7: The effects of the village intervention on fertiliser use of farmers (kg/acre)

	(1)	(2)	(3)
Variable	Full sample	Fertiliser users	Fertiliser non-users
Village treatment	5.645**	7.109**	2.434*
	(2.504)	(3.345)	(1.332)
Baseline controls	Yes	Yes	Yes
Mean dep. var.	11.988	18.595	2.300
Observations	972	580	392
R-Squared	0.089	0.073	0.039

Note: This table presents the results of an OLS regression following Specification 3. The dependent variables is the amount of fertiliser use (of all types) per acre. Control variables include baseline measures of sex, age, education, land owned, farm experience, risk aversion, number of household members and number of markets visited. Column (1) present the results of the analysis sample (balanced panel between base and phone endline survey); Column (2) present the results for those farmers who used fertiliser before and Column (3) presents the results for those farmers who have not used fertiliser before. Errors are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.01$.

Table 8: The effects of the village intervention on the agricultural investment and outcomes

Variable	(1) Maize acres (acres)	(2) Use of agro-chemicals (1 = yes; 0 = no)	(3) Use of hybrid variety (1 = yes; 0 = no)	(4) Harvest (kg)
Village intervention	-0.0921	-0.0651	0.185	192.0
	(0.329)	(0.0918)	(0.114)	(279.4)
Baseline controls	Yes	Yes	Yes	Yes
Mean dep. var.	1.6170	0.47312	0.50538	1123.5
Observations	211	179	179	178
R-Squared	0.368	0.117	0.112	0.155

Note: This table presents the results of an OLS regression of various variables following Specification 3. The dependent variables refer to the (in-person) endline variables. Baseline control variables include baseline measures of sex, age, education, land owned, farm experience, risk aversion, number of household members, number of markets visited and baseline beliefs. Sample only includes the balanced sample between baseline line and endline in person survey. Columns (2), (3) and (4) refer to input use on maize and are conditional on cultivating maize. Errors are clustered at the village level. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$.

Table 9: The effects of the market intervention on agro-dealer prices

Variable	(1) Urea price (TZS/50 kg)	(2) WTP (TZS)
Market intervention	2,219	35,349
	(1,778)	(27,115)
Baseline controls	Yes	Yes
Mean dep. var.	57,829	47,950
Observations	149	160
R-Squared	0.081	0.065

Note: This table presents the results of an OLS regression following Specification 4. The sample is the balanced panel between base and in-person endline survey (only including those agro-dealers who reported prices in column (1)). Control variables include: Sex owner, education owner, age owner, TFRA licence, Tagmark membership, asset index, total current capacity and years selling fertiliser. Note that the current capacity variable is not available for those agro-dealers who at baseline did not sell fertilisers. Market level clustered standard errors reported in parenthesis. *** p< 0.01, ** p< 0.05, * p< 0.01.

Table 10: The effects of the market intervention on agro-dealer sales

Variable	(1) Ever sold urea (1 = yes ; 0 = no)	(2) Urea in stock (1=yes ; 0 = no)	(3) Quantity urea sold (kg/year)	(4) Fertilizer sold (kg/year)	(5) Quantity urea sold (kg/year)	(6) Fertilizer sold (kg/year)
Market intervention * After	0.0588	0.0305	15,068	16,961	14,808	15,969
	(0.0476)	(0.0937)	(10,296)	(25,433)	(10,602)	(31,091)
Market intervention	-0.0267	-0.0735	-2,155	2,818	-2,966	3,370
	(0.0387)	(0.0744)	(4,825)	(10,300)	(5,343)	(12,319)
After	-0.0917**	-0.351***	4,314	21,399	5,029	28,644
	(0.0367)	(0.0736)	(6,482)	(20,393)	(7,194)	(25,027)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	320	320	284	320	256	260
R-squared	0.097	0.190	0.347	0.437	0.351	0.447

Note: This table presents the results of an OLS regression following a difference-in-difference specification. The sample is the balanced panel in columns (1) through (4). Columns (5) and (6) limit the sample further to those agro-dealers who sell fertilisers in both periods. Control variables include: Sex owner, education owner, age owner, TFRA licence, Tagmark membership, asset index, total current capacity and years selling fertiliser. Note that the current capacity variable is not available for those agro-dealers who at baseline did not sell fertilisers. Market level clustered standard errors reported in parenthesis. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$.

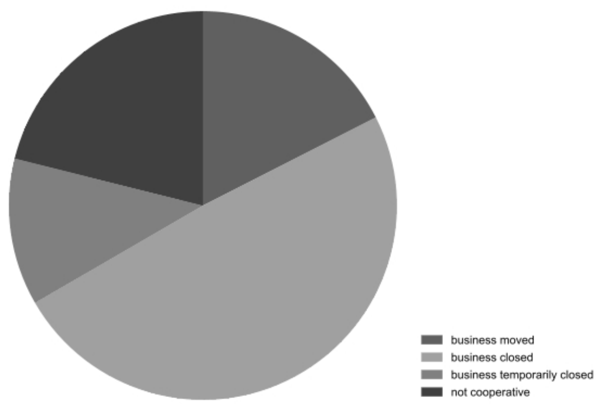
Table 11: The effects of the market intervention on agro-dealer sales: Mean Bayesian posterior distribution of treatment effects

	(1)	(2)	(3)	(4)	(5)
Variable	Avg. Treatment Effect (µ1 - µ2)	HDIlo	HDIhigh	Prob< 0	Prob0 >
(1) Sold Urea (1 = yes; 0 = no)	0.01	-0.07	0.09	43.2%	56.8%
(2) Urea In Stock (1 = yes; 0 = no)	-0.0287	-0.121	0.0671	72.6%	27.4%
(3) Quantity Urea Sold (kg/year)	452	-226	1120	9.2%	90.8%
(4) Fertilizer Sold (kg/year)	-205	-870	458	73.0%	27.0%
(5) Quantity Urea Sold (kg/year)	-358	-1120	393	82.3%	17.7%
(6) Fertilizer Sold (kg/year)	1410	-372	3170	5.8%	94.2%

Note: This table presents the results of a Bayesian hierarchical model. The sample is the balanced panel in rows (1) through (4). Rows (5) and (6) limit the sample further to those agro-dealers who sell fertilisers in both periods. Column (1) presents average treatment effect, Columns (2) and (3) present the 95% Highest Density Interval (HDI) which indicates the most likely estimated parameter values that comprise 95% of the distribution of possible effects. Columns (4) and (5) present the respective probabilities that the true effect is less than or greater than zero.

Data Appendix

Figure A.1: Reasons why baseline agro dealers were not interviewed at endline



Note: There are many reasons why a dealer interviewed at baseline would no longer be interviewed at endline. We asked the enumerators to record this reason at endline. This [pie diagram gives an overview of the reasons. One can see that in the majority of cases, the business was closed or temporarily closed.

Figure A.2: Histograms of farmer-reported beliefs about fertilizer quality presented by whether the farmer had ever purchased fertilizer previously (bad quality bags out of ten). Past fertiliser use is captured by past purchases. Balanced panel (analysis sample).

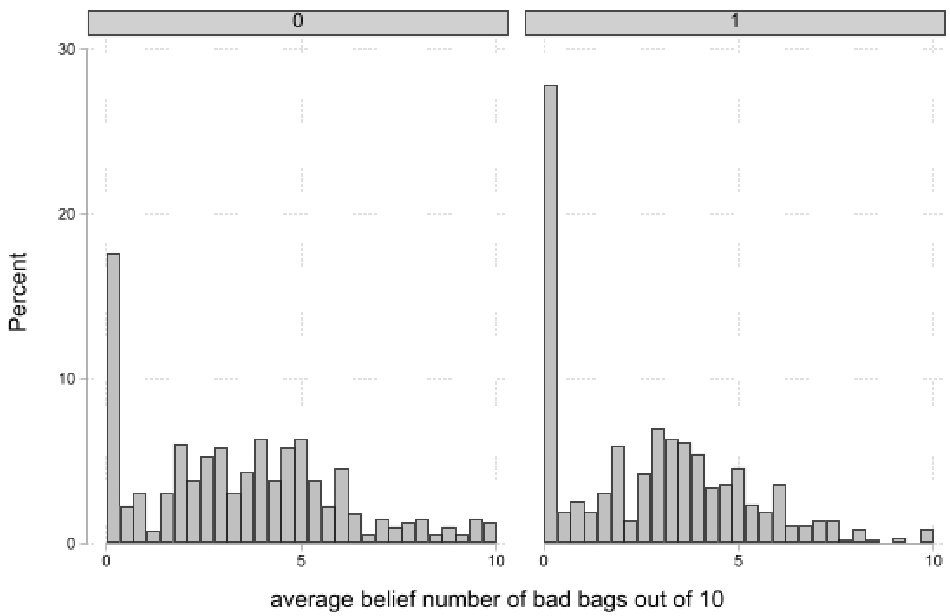


Figure A.3: Kernel density amount of urea sold kg/year by market treatment status at endline, agro-dealer data

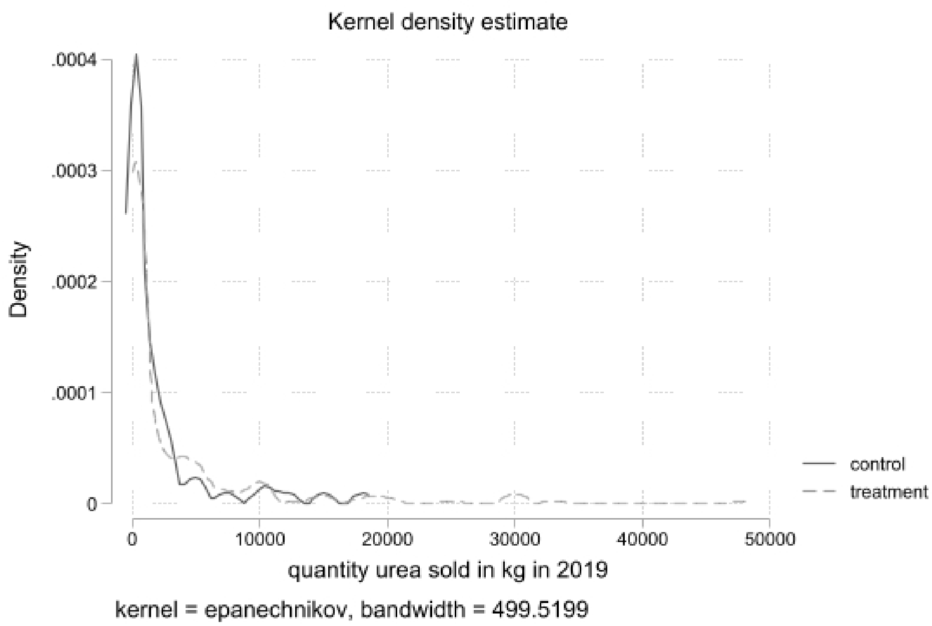


Table A.1: Test for differential attrition in the farmer sample

Variables	Interviewed via phone	Interviewed in person
Village intervention	0.01864	0.00111
	(0.02244)	(0.01852)
Constant	0.6635***	0.14819***
	(0.01727)	(0.01299)
Observations	1,479	1,479
R-Squared	0.00	0.00

Note: This table regresses presence in the endline survey on the village intervention variable. Robust standard errors are reported in parenthesis. *** p< 0.01, ** p< 0.05, * p< 0.01

Table A.2: Regression of fertiliser use on farmer characteristics at baseline

	(1) Ever purchased fertiliser (1 = yes ; 0 = no)	(2) Purchased urea (1 = yes ; 0 = no)	(3) Fertiliser purchased per acre (kg/acre)
Respondent sex (0 = male; 1 =female)	-0.0326	0.0185	-4.642
	(0.0387)	(0.0373)	(6.533)
Respondent age	0.000670	-0.00211	0.269
	(0.00165)	(0.00146)	(0.237)
Primary education dummy	-0.0282	0.0362	-6.836
	(0.0688)	(0.0562)	(7.362)
Secondary education dummy	0.115	0.0856	-8.684
	(0.0734)	(0.0731)	(9.364)
Land (acres)	-3.91e-05	0.00372*	0.301
	(0.00198)	(0.00202)	(0.458)
Farming experience (years)	-0.00130	0.00142	-0.172
	(0.00168)	(0.00143)	(0.275)
Risk loving*	0.0270**	0.0127	-0.296
	(0.0114)	(0.0112)	(1.977)
Household members	-0.00629	-0.00490	-0.0944
	(0.00688)	(0.00742)	(1.067)
Number of markets visited	0.111***	0.0974***	7.025
	(0.0206)	(0.0197)	(4.302)
Constant	0.773***	0.734***	24.82
	(0.124)	(0.108)	(16.12)
Village fixed effects	Yes	Yes	Yes
Observations	978	978	400
R-squared	0.422	0.457	0.419

Note: This table regresses fertiliser purchasing and use at baseline on farmer characteristics at baseline for the balance panel (analysis sample). Column (3) represents purchases per acre conditional on any purchases made (in the main growing season in 2018).* Risk loving refers to the categorical answer to the question 'compared to others, how much risk do you take'. Answers are coded from 1 = much fewer, to 5 = much more. Errors are clustered at the village level and reported in parenthesis. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$.

Table A.3: Descriptive statistics of markets at baseline

	Control markets	Treatment markets	P-value
Number of sellers/market	2.41 (1.82)	4.34 (5.21)	0.03
Number of markets	46	43	

Note: This sample includes all markets where agro-dealers have been interviewed at baseline. Standard deviations are added in parenthesis.

Table A.4: Overview of market churning and attrition; identification of the analysis sample

Analysis sample	Characteristics	Number of dealers	Percentage of the sample
No	new firm in 2019 - not selling in 2019	83	19
No	new firm in 2019 - selling in 2019	49	11
Yes	not selling in 2018 – interviewed and selling in 2019	28	6
Yes	not selling in 2018 - interviewed and still not selling in 2019	49	11
No	not selling in 2018 - not interviewed 2019	34	8
Yes	selling 2018 - interviewed in 2019 and no longer selling in 2019	17	4
Yes	selling 2018 - interviewed in 2019 and still selling in 2019	138	33
No	selling 2018 - not interviewed in 2019	32	7
		430	100

Note: We define the analysis sample as agro-dealers who were interviewed in both rounds. This sample consists of 232 agro dealers. Note also the 132 additional agro-dealers at endline. Some of these might not be new firms but rather related to issues in the data collection process. We distinguish between two cases. First, the dealers whom should have been interviewed at baseline but were not, because no-one was available at the time. We find 22 agro dealers at endline which should have been included at baseline as they had been in existence for a more than one year at endline. Second, our definition of agro dealers changed between the two rounds. The revised set of criteria aimed to include all shops who sold fertiliser in the past, sold fertiliser this year, and considers selling fertiliser in the future. As the latter is somewhat subject to interpretation, and the former might be subject to recall, errors are still expected. During the endline, we noted the presence of 22 new agro dealers who had never sold in the past, are not currently selling, and do not plan to sell (and hence should not have been included in either data collection round).

Table A.5: Test for differential attrition in the agro-dealer sample

	Interviewed at endline
Market intervention (1=yes ; 0 = no)	0.06
	(0.05)
Constant	0.73***
	(0.00)
Observations	298
R-Squared	0.00

Note: This table regresses presence in the (in-person) endline survey on the market intervention variable using a linear specification. Robust standard errors are reported in parentheses. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$

Table A.6: Regression of fertilizer beliefs on farmer characteristics at baseline

	(1)	(2)
Variable	Number of bad quality bags (out of ten)	Farmer has any concern about fertiliser (yes = 1 ; no = 0)
Respondent sex (0 = male; 1 =female)	-0.370*	-0.0761**
	(0.202)	(0.0352)
Respondent age	-0.0118	-0.00290*
	(0.00942)	(0.00169)
Primary education dummy	0.192	0.0410
	(0.347)	(0.0660)
Secondary education dummy	0.588	0.0589
	(0.442)	(0.0793)
Land (acres)	0.0193*	0.00142
	(0.0117)	(0.00130)
Farming experience (years)	-0.00403	0.000268
	(0.00980)	(0.00167)
Risk loving*	-0.113	-0.0248**
	(0.0708)	(0.0122)
Household Members	0.0227	0.000496
	(0.0381)	(0.00568)
Number of markets visited in past 12 months	-0.0258	0.0236
	(0.122)	(0.0197)
Ever purchased fertiliser (1 = yes; 0 = no)	-0.653***	-0.111***
	(0.226)	(0.0380)
Constant	3.394***	0.893***
	(0.671)	(0.119)
Village fixed effects	Yes	Yes
Observations	969	969
R-squared	0.219	0.191

Note: This table regresses baseline beliefs on baseline farmer characteristics for the analysis sample (balanced panel). * Risk loving refers to the categorical answer to the question ‘compared to others, how much risk do you take’. Answers are coded from 1 = much fewer, to 5 = much more. Errors are clustered at the village level and reported in parenthesis. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$.

Table A.7: Regression of fertiliser beliefs on market characteristics at baseline

Variable	(1) N bad quality bags (out of ten)	(2) N bad quality bags (out of ten)	(3) N bad quality bags (out of ten)	(4) N bad quality bags (out of ten)
Distance to market (km)	3.26e-06	2.42e-05	-0.000272	-0.000486
	(0.00109)	(0.00107)	(0.00126)	(0.00127)
N of agro-dealers selling in both rounds	-0.0457	-0.0197	-0.0888	-0.0749
	(0.0534)	(0.0532)	(0.0668)	(0.0663)
N of agro-dealers	-0.0494**	-0.0521***	-0.0295	-0.0316
	(0.0201)	(0.0199)	(0.0248)	(0.0247)
Order market elicited	0.224***	0.126**	0.207***	0.164**
	(0.0477)	(0.0491)	(0.0630)	(0.0644)
Dummy for weekly visits to market		0.628		0.347
		(0.489)		(0.558)
Dummy for monthly visits to market		0.374		0.894
		(0.529)		(0.572)
Dummy for quarterly visits to market		0.385		0.139
		(0.425)		(0.496)
Dummy for yearly visits to market		0.284		0.418
		(0.426)		(0.536)
Dummy for never having visited market		0.878**		0.592
		(0.418)		(0.491)
Did farmer purchase at market before?			-0.419***	-0.200
(1=yes; 0=no)			(0.149)	(0.170)
Constant	3.048***	2.519***	2.913***	2.498***
	(0.103)	(0.420)	(0.139)	(0.489)
Observations	2,428	2,428	1,474	1,474
Number of farmers	982	982	587	587
R-squared	0.0236	0.0300	0.0204	0.0230

Note: This table presents the results of a farmer-fixed effect regression of market/farmer level baseline beliefs (number of bad quality bags) on market characteristics at baseline. Columns (1) and (2) are the analysis sample (balanced panel). Columns (3) and (4) limit the sample to farmers who made fertiliser purchases in the past. further conditional on having purchased fertiliser in the past. The base category of the visits is daily visits. Robust standard errors are reported in parentheses. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$.

Table A.8: Regression of fertiliser purchases on market characteristics at baseline

Variable	(1) Purchase (1=yes; 0=no)	(2) Purchase (1=yes; 0=no)	(3) Purchase (1=yes; 0=no)	(4) Purchase (1=yes; 0=no)
Distance to market (km)	-0.000649*	0.000246	0.0001572	0.0003435
	(0.000376)	(0.000240)	(0.0003428)	(0.0003431)
N of agro-dealers selling in both rounds	0.0763***	0.0259**	0.0131681	0.0293655
	(0.0188)	(0.0120)	(0.0160445)	0.0186549
N of agro-dealers	-0.000162	-0.000855	0.0009097	0.0018167
	(0.00511)	(0.00332)	(0.0043618)	(0.0055472)
Dummy for weekly visits to market		0.211	0.496**	0.098
		(0.170)	(0.223)	(0.219)
Dummy for monthly visits to market		0.193	0.418*	0.065
		(0.184)	(0.239)	(0.245)
Dummy for quarterly visits to market		0.229	0.551**	0.077
		(0.159)	(0.222)	(0.199)
Dummy for yearly visits to market		-0.0279	0.2740	-0.2675
		(0.172)	(0.234)	(0.240)
Dummy for never having visited market		-0.508***	-0.225	-0.634***
		(0.158)	(0.220)	(0.200)
Constant	0.157***	0.461***	0.196	0.556***
	(0.0186)	(0.156)	(0.217)	(0.199)
Observations	1,150	1,150	671	379
Number of farmers	407	407	240	132
R-squared	0.1215	0.5406	0.5646	0.5343

Note: This table presents the results of a farmer-fixed effect regression of market/farmer level baseline purchases on market characteristics at baseline. Columns (1) and (2) are the analysis sample (balanced panel) conditional on having purchased fertiliser in the past. Columns (3) and (4) present sub-sample analysis for those farmers who purchase less urea than the median (Column (3)) and more urea than the median (Column (4)). The median is established using urea purchases in the last (long rain) growing season. The base category of the visits is daily visits. Robust standard errors are reported in parentheses.*** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$.

Table A.9: The effects of the village intervention on the beliefs of farmers, village-level analysis

	(1)	(2) (3)	
variables	Mean village beliefs	St. Dev. village beliefs	St. Dev / Mean village beliefs
Village intervention * After	-0.586**	-0.169	0.272***
	(0.252)	(0.151)	(0.0964)
After	-0.605***	-0.0610	0.242***
	(0.185)	(0.111)	(0.0631)
Village intervention	0.0359	-0.00926	-0.0287
	(0.160)	(0.0946)	(0.0427)
Constant	3.089***	2.314***	0.813***
	(0.121)	(0.0622)	(0.0298)
Mean dep. var.	3.10	2.30	0.79
Observations	292	289	285
R-squared	0.174	0.021	0.233

Note: This table presents the results of an OLS regression of the village-level mean (Column (1)) and the standard deviation (Column (2)) of the number of bad bags (out of ten), and the ratio of these two variables (Column (3)) using a difference-in-difference specification. The regression is weighted by the number of observations we have for each village (it should be ten but some people note don't know in the beliefs section). Robust standard errors are reported in parenthesis. *** p< 0.01, ** p< 0.05, * p< 0.01.

Table A.10: The effect of the village intervention on (non-urea) fertiliser purchases

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Variable	DAP (kg)	DAP (0/1)	CAN (kg)	CAN (0/1)	Minjinju (kg)	Minjinju (0/1)	NPK (kg)	NPK (0/1)	SA (kg)	SA (0/1
Village int.*After	0.784	0.0165	-0.936	0.000117	0.548	0.00823	-1.048	0.00413	-1.265	-0.0163*
	(4.545)	(0.0266)	(2.483)	(0.0204)	(0.747)	(0.00939)	(1.729)	(0.00900)	(1.104)	(0.00954
After	-2.078	-0.0389**	-1.209**	-0.0287**	-1.277**	-0.0164**	-0.818*	-0.0123*	-0.105	-0.00205
	(3.755)	(0.0180)	(0.582)	(0.0118)	(0.616)	(0.00746)	(0.439)	(0.00628)	(0.317)	(0.00546
Village int.	-0.920	0.00495	3.140	0.0311	-0.614	-0.0106	1.261	-0.000440	0.722	0.00802
	(3.085)	(0.0278)	(2.275)	(0.0222)	(0.700)	(0.00898)	(1.481)	(0.00949)	(1.202)	(0.0138)
Observations	1,956	1,956	1,956	1,956	1,956	1,956	1,956	1,956	1,956	1,956
R-Squared	0.087	0.061	0.036	0.039	0.028	0.049	0.041	0.014	0.007	0.016

Note: This table presents the results of an OLS regression following a difference-in-difference specification. The dependent variables are a binary measure capturing whether the farmer purchased a certain type of fertiliser in the previous growing season, and the amount of purchased (kg) in the previous growing season. Baseline control variables include baseline measures of sex, age, education, land owned, farm experience, risk aversion, number of household members and number of markets visited. The analysis sample (balanced panel). Errors are clustered at the village level and reported in parenthesis. *** p< 0.01, ** p< 0.05, * p< 0.01.

Table A.11: The effects of the village intervention on farmer prices

Variables	(1) Price Urea (TS/kg)	(2) Price DAP (TS/kg)	(3) Price CAN (TS/kg)
Village intervention	-7.259	-282.2	-132.5
	(49.69)	(197.6)	(130.6)
Baseline controls	Yes	Yes	Yes
Mean dep. var	1,295	1,529	1,255
Observations	367	92	37
R-Squared	0.071	0.083	0.371

Note: This table presents the results of an OLS regression using Specification 3 of the price of fertiliser on the village intervention with baseline control variables. Baseline control variables include baseline measures of sex, age, education, land owned, farm experience, risk aversion, number of household members and number of markets visited. The analysis sample (balanced panel). Errors are clustered at the village level and reported in parenthesis. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$.

Table A.12: Correlation between week and price indicators of the agro-dealers

Variable	(1) Urea price (TS/kg)	(2) NPK price (TS/kg)	(3) DAP price (TS/kg)	(4) Customers	(5) Customers fertilizer
Week	-4.757*	3.367	-4.136	6.295	-1.093
	(2.712)	(8.704)	(4.256)	(5.061)	(0.754)
Market intervention * Week	2.857	9.911	16.78**	4.239	3.152*
	(4.357)	(11.00)	(7.965)	(7.873)	(1.706)
Constant	1,333***	1,456***	1,488***	95.09***	15.64**
	(15.36)	(37.24)	(30.53)	(27.59)	(6.408)
Mean dep. var.	1,311	1,520	1,528	154	20
Observations	506	301	371	510	910
Number of agro-dealers	69	50	54	70	70
R-Squared	0.017	0.044	0.078	0.018	0.007

Note: This table presents the results of an agro-dealer fixed-effects regression mapping measures elicited during the weekly agro-dealer phone survey on the market intervention and and the week of elicitation. The sample consists of the dealers whom responded to all weeks of the survey and is limited to the weeks from mid December until mid March. Robust standard errors are reported in parenthesis. ***p< 0.01, ** p< 0.05, * p< 0.01.

Table A.13: Correlation between week and sales indicators of the agro-dealers

Variable	(1) Fert sold (per week, kg)	(2) Urea sold (per week, kg)	(3) DAP sold (per week, kg)	(4) NPK sold (per week, kg)
Week	1,327	1,661	-18.62	2,041
	(1,191)	(1,495)	(13.23)	(1,914)
Market intervention * Week	-1,276	-1,651	-24.53	-1,998
	(1,191)	(1,495)	(43.81)	(1,915)
Constant	-2,403	-3,303	542.3***	-3,461
	(3,800)	(4,634)	(182.8)	(5,928)
Mean dep. var.	2,018	1,883	302	3,022
Observations	438	260	191	478
Number of agro-dealers	67	49	43	70
R-squared	0.033	0.062	0.050	0.031

Note: This table presents the results of an agro-dealer fixed-effects regression mapping measures elicited during the weekly agro-dealer phone survey on the market intervention and and the week of elicitation. The sample consists of the dealers whom responded to all weeks of the survey and is limited to the weeks from mid December until mid March. Robust standard errors are reported in parenthesis. ***p< 0.01, ** p< 0.05, * p< 0.01.

Table A.14: Changes in farmer beliefs across markets

Variables	(1) N bad quality bags (out of ten)	(2) N bad quality bags (out of ten)	(3) N bad quality bags (out of ten)
Distance to market (km)	-0.00704	-0.00782*	-0.00906*
	(0.00452)	(0.00457)	(0.00543)
N of agro-dealers selling in both rounds	0.165	0.194	0.250
	(0.174)	(0.180)	(0.225)
N of agro-dealers	-0.0412	-0.0523	-0.0783
	(0.0483)	(0.0485)	(0.0606)
Farmer visits market at baseline (1=yes; 0=no)		0.119	0.246
		(0.381)	(0.555)
Farmer purchases at market at baseline (1=yes; 0=no)			-0.454
			(0.612)
Constant	3.006***	3.135***	2.946***
	(0.0928)	(0.115)	(0.156)
Observations	862	862	531
Number of farmers	219	219	133
R-squared	0.0166	0.0218	0.0164

Note: This table presents the results of a farmer-fixed effect regression of market-level beliefs (number of bags with bad quality fertiliser - out of ten) on market characteristics at baseline (Column (1)), whether or not the farmer had visited the market at baseline (Column (2)) and whether or not the farmer had purchased fertiliser at the market at baseline (Column (3)). Column (3) is conditional on having purchased fertiliser before. The coefficients presented in this table are the interaction coefficients with the village intervention variable (the regression controls for the same set of variables, not interacted with the village treatment. These coefficients are not reported in this table). Sample: farmers present at both baseline and in-person endline. Robust standard errors are reported in parenthesis.***p< 0.01, ** p< 0.05, * p< 0.01.

Table A.15: Changes in farmer visits and purchases across markets

Variables	(1) N of market visited	(2) Visit local market (1=yes; 0=no)	(3) Distance travelled to purchase (km)	(4) Purchase at local market (1=yes; 0=no)
Village intervention	-0.0742	0.0723	-14.86**	0.106
	(0.198)	(0.0746)	(6.858)	(0.0658)
Baseline dep. var.	0.233***	0.757**	0.479***	0.4777***
	(0.0594)	(0.0727)	(0.156)	(0.603)
Baseline controls	Yes	Yes	Yes	Yes
Mean dep. var. at baseline	1.39	0.61	25.45	0.4
Observations	214	179	226	291
R-squared	0.177	0.614	0.376	0.302

Note: This presents the results of an OLS regression following an ANCOVA specification using the analysis sample (balanced sample between base and phone/in-person endlin). Columns (1) and (2) use the endline in person data. Columns (3) and (4) use the endline phone data. Control variables include baseline measures of sex, age, education, land owned, farm experience, risk aversion and the number of household members (but not the number of markets visited at baseline). Columns (3) and (4) limit the sample to farmers who made fertiliser purchases in the past. Errors are clustered at the village level.***p< 0.01, ** p< 0.05, * p< 0.01.

Ethics Appendix

In this appendix, we discuss ethics-related components of our study. We follow elements of the Belmont Report of 1978 (see Glennerster and Powers (2016) for a useful introduction), and use the suggestions of Asiedu et al. (2021) to guide our discussion.

Policy equipoise

While our study finds sizable positive effects on the beliefs of farmers, and establishes impacts on their behaviour which are likely to result in increased crop yields, profits, and incomes, it is important to note that at the time of conducting the experiment, we did not expect such a positive impact. Let us clarify: we conceived of the experiment after the unexpected results of a previous study in the area, as documented in Michelson et al. (2021). In that study, we found that fertiliser in the region, contrary to our hypothesis and contrary to the stated beliefs of the majority of farmers we had worked with, was of good quality. We had expected to find problems in the quality and we had proposed a research project to document the source of the quality problem in the fertiliser supply chain. Following this unexpected good quality result, we applied for permission from the funder (PEDL) to use the remainder of funds to bring this research finding back to the research participants.[26] We proposed a randomized controlled trial to allow us to study the effects of this information provision.

It is important to note that at the time of this proposal, it was well established that information constraints among farmers were critical, and a real impediment to technology adoption (see among others, Foster and Rosenzweig (2010); Sunding and Zilberman (2001)). However, while experiments providing information to farmers have had some success changing beliefs, there is less evidence regarding those belief changes affecting actions and outcomes. In effect, researchers have documented a pattern of null-effects, in some cases precise and in others under-powered (see, among others Aker (2011); Jensen, Barrett and Mude

[26]See the PEDL entry of our prior project: Misperceived Quality: Fertilizer in Tanzania — PEDL (cepr.org)

(2016); Magruder (2018); Harou et al. (2022)).

As such, we meet the criteria of policy equipoise, in the sense that there was credible uncertainty regarding the effectiveness of this information treatment. Further taking into consideration the cost of publicly providing this information results in a likely negative overall impact of the information treatment.

Researcher's role regarding implementation of the program

In this study, we both implemented the information intervention as well as evaluated the program. The role of active researcher was inevitable: there were no existing programs in place in Tanzania which were engaged in the type of information provision we had in mind. More importantly, the information to be provided was generated by a prior research project, and hence the most credible providers would be the researchers themselves.

We did however, separate the roles of implementer and evaluator on the field in numerous ways. At any point in time, we had two teams on the ground. One team conducted the interviews, and one team conducted the intervention, with the interviewing team always arriving and finishing their activities prior to the intervention team. We completed the interviews prior to the interventions because we needed to elicit pre-intervention agro-dealers' and farmers' beliefs and behaviour.

Potential harm to participants and non-participants from the intervention

We agree with Barrett and Carter (2020) that the use of randomization increases the potential to harm research participants, and this concern was on the forefront of our minds when designing our study.

Providing potentially useful information to only a subset of participants not only deprives the non-participants of this information but also might, through subsequent behavioural changes, negatively impact non-participants. As such, the principle justice, or the fair allocation of risks and benefits was critical in our design, and in particular the level of randomization employed. Beneficence, or the principle that researchers should seek to increase people's well-being and avoid knowingly doing harm, guided our follow-up data collection tools.

Randomization was implemented at the village-market level. This implies that a village-market cluster either belonged to treatment or control. This design ensured that the information farmers received was consistent, i.e., the same information was provided at their local market as well as in the village. It also avoided feelings of jealousy within the village. To this end, we should note that after the ten interviews were completed, we invited all farmers in the village to a common location, such as outside the village office, and conducted the information meetings. So the information intervention did not exclude any village farmer, and was not exclusively tailored to any interview subjects.

We acknowledge the possibility that agro-dealers in control markets are negatively impacted by our information intervention. While the Tanzanian government imposes strict limits on pricing, preventing any upward push on prices which might negatively impact the farmers, there are no limits on how much an agro-dealer can sell. This implies that a farmer in a treatment village might not only respond to our information treatment by increasing the amount of fertiliser purchased, but also by switching agro-dealers, from a control to a treatment market. This switch might, in its turn, negatively impact the agro-dealers in the control market.

We set up our design and data collection to minimize such risk.

First, at the time of data collection, evidence indicated that farmers conduct most purchases locally and did not tend to switch markets. Focus groups with farmers before the baseline survey suggested that farmers visit only one or two proximate markets and would be unlikely to travel to a more distant market. We therefore did not anticipate farmers would reallocate their purchasing to new markets. It was our expectation that should farmers increase purchasing they would buy more at their usual market.

Second, while conducting the information meeting, emphasis was placed on the local market (which also received the information treatment). However, in the question and answer after each meeting, participants could request information on other markets. At no point were participants deceived. Correct information was provided about all markets that participants asked about. Thus, if farmers requested information on a market other than their local market, correct information was provided on this market. This policy not only avoided any form of deception (as in Wilson 2014), but also might have prevented market switches.

Third, we collected sales data from the agro-dealers on a weekly basis via the phone from the moment the agro-dealer was included in this survey. These data allowed us monitor the situation and to track impacts in real time, allowing us to respond in case we observed a marked post-treatment drop in sales in control markets. We recognise that this method is not fool-proof. Indeed both an increase in sales in the treatment market, and well as a re-allocation of customers between treatment and control markets, could result in a widening gap in sales between treatment and control markets. Combined with the other measures in place, it was an additional source of monitoring.

Fourth, as detailed in Section (7), we expanded the treatment to the control markets within the same calendar year, prior to the next agricultural season.

Finally, one might be concerned that our information intervention could encourage to agro-dealers to start adulterating the fertilisers. As we noted in Michelson et al. (2021) we thought this was highly unlikely. The most common fertiliser, urea, cannot be profitably adulterated at the agro-dealer level given that any substitutes available, such as salt, are more expensive at current (local) market prices. To further deter the agro-dealers, all were informed at the time of the baseline survey that our research team was collecting samples of fertilisers in the region in a randomized manner . However, to monitor the situation, we followed our research protocols established in Michelson et al. (2021) and had mystery buyers visiting a randomly selected 45 agro-dealers in both treatment and control markets. We tested these urea fertiliser at a laboratory at the University of Illinois and, yet again, established that 100% of the fertiliser samples met international standards.

Potential harm from data collections and research protocols

Respect for persons implies that research participants' autonomy must be respected. Research participant must give informed consent to participate in the study. We followed the informed consent protocols outlined by the IRB protocol at the University of Illinois whom approved the design . We informed the research participants about the goals of the study, the risk and benefits associated with the study, and how their data would be processed. Consent was obtained verbally, given the high levels of illiteracy in the area.

We agree with Josephson and Smale (2021) in that while the IRB board did not consider the participants of our study to be vulnerable, the fact that we are working with impoverished, illiterate population defers a degree of responsibility. We carefully trained the enumerator team over the course of a full week in all aspects of ethical data collection, and requested each and every researchers in the study, whether principle investigator or enumerator to complete an IRB training.

Both our enumerator and intervention team were graduates and students from Sokoini Agricultural University. As such, they were fluent in the local language, Kiswahili. All interviews and interventions were conducted in this local language, Kiswahili.

We agree with Kaplan at al. (2021) that respect for persons also includes the enumerator team. While the principle investigator from Sokoini Agricultural University was an early career researcher at the time of our study, still, a power hierarchy between the investigator and the rest of the research team might have existed. To create a professional environment, we hired several experience team leaders.

Our data collection adhered to the standard requirements for privacy and confidentiality as outlined by the IRB protocol of the University of Illinois. All efforts were made to conduct the interviews privately, in the compound of the respondent. No personal special category information, or sensitive data, was collected, such as information on race, sexuality or political information.

While individual identifying data was collected at baseline, with the purpose of conducting a panel study, the resulting report does not include any such information and the publicly available dataset shared via FIGSHARE has all such information removed. Hard-copy data which contains individual identifying variables is stored securely, on campus, at the University of Sokoini.

Financial and reputational conflict of interest

We did not anticipate any direct conflict of interest. The researchers involved in this study are not connected to any government agency involved in fertiliser testing or regulation. Nor do the researchers involved in this study have any secondary appointment which brings them into a position of conflict with the study.

To ensure research transparency and replicability, we developed a pre-analysis plan. This plan was developed after the baseline took place, but before the endline. While we did not register this plan on any of the standard registers, such as the American Economic Association RCT registry or the 3IE registry, the British Research Registry or OFS, we recorded our plans with the funder, PEDL.

Following a pre-analysis plan protected us from some of the main ethical concerns at the analysis stage, such as p-hacking, data mining and specification search (Lybbert and Bucola 2021). This pre-analysis plan, included in this appendix, covered the main regression specifications to be executed using the various sources of data. The current working paper draft follows the pre-analysis plan closely and all regressions establishing impact were pre-identified. The only specifications omitted from the working paper were those where data quality and attrition concerns were too considerable to warrant their inclusion. We found this process to facilitate our data analysis. Only the exploratory analysis of base and endline deviates from what was originally specified.

We made our data and data instruments available via FIGSHARE. We made the study replication files available to the publishing journal. Finally, we applied for open access for our research paper.

Feedback to participants and communities

Our study constituted of feeding back information from a prior study to the original communities covered in Michelson et al. (2021) study. It should be noted though that the sample of farmers in this study was not the same as the prior study. This study used a large, representative, sample of farmers.

Immediately after completing our endline survey, we implemented the information treatment among the control markets. We employed the same methods as in the original intervention and distributed pamphlets and posters to all remaining agro-dealers in all remaining control markets. This work was funded by the Sussex University Impact Acceleration Fund.

Foreseeable misuse of research results

We do not anticipate any misuse of our research results. However, to further prevent the accidental misunderstanding of our research results, we worked with the communications departments of our respective universities to draft a press release. Drafting the press release together with us resulted in accurate information to be released to the media. We conclude with one final note on our research design which we have not yet covered in any of the seven sections above. And this is that we had set up the intervention itself (and not just the data collection) with a goal towards replication. Our intervention was simple and standardized across locations. The village implementation followed standard practices of the government extension services who regularly go into villages to provide information sessions. As such, our intervention could be easily integrated into the existing government extension framework. The market intervention could be integrated in the existing system as well, in particular, within the Tanzanian Fertilizer Regulatory Authority which registers agro-businesses and sets fertiliser pricing. While this choice for simplicity limited what we could test for empirically, this choice was made in a conscious manner (as implied by Khosrowi 2022)

Intervention Appendix

To help us design the intervention, we conducted two focus group interviews with 40 farmers in the region in two non-sample villages in the Singida region in November of 2018. We asked if we had information to share about fertiliser quality, how best should we share this with farmers. Farmers noted the importance of large colourful posters in the market, and information at the point of purchase – agro dealers' shop counters and windows. At the time, we were considering a range of communication methods, including media and phone-based methods. However, our focus group interviews, and our baseline survey results confirmed that farmers in this region rely mostly on face-to-face provided information, and generally do not get their information about agricultural inputs from the radio or via the phone. The focus group interviews and baseline survey also indicated that organising village meetings would require involving the local government extension agent as this individual is largely perceived to be a trusted person.

Both enumerator and intervention teams were graduates and students from Sokoine Agricultural University, a public University based in Morogoro, Tanzania. The university is an established and well-respected agricultural university in Sub-Saharan Africa, with extensive experience in agricultural technology development, such as hybrid seeds, and extension. As such, they were familiar with the research protocols established, and fluent in the local language, Kiswahili. We conudcted all interviews and the information related to the market and village interventions in Kiswahili. We hired a total of 17 enumerators and 4 supervisors and took one week to train them. The purpose of intervention training was to introduce the research project to the team so that they could effectively answer questions when asked by respondents (farmers and agro-dealers). Some of the enumerators had worked on the original 2015/16 study collecting the fertiliser samples. Enumerators were trained to follow the research ethics and protocol; how to distribute pamphlets and posters and to interview agro-dealers. We conducted another training for the farmers' and dealers' survey, how to ask the questions and how to complete the questionnaire with farmers. Finally, we trained four supervisors on research ethics, protocols and distribution of roles. While we used pen and paper surveys at baseline, we collected data via tablets at endline.

When the intervention team approached the agro-dealers, they used the following script.

"We are from Sokoine University of Agriculture (SUA). We have some important information for you. In 2016, urea samples were taken from this market for testing. Results show that fertilizer tested contained 46% Nitrogen which is required. We have come with signs (see Picture A.4) to be displayed in your shop and we will also display the same around this market/village. We are also requesting to distribute the pamphlets to customers/farmers who come to your shop (see Picture A.5). Further fertilizer testing will also be done in June 2019."

When conducting the village interventions, the supervisors read the following script:

"Fertiliser is one of the important inputs in agricultural production. We have different brands and types of fertiliser. Which types of fertiliser do you use? [Ask responses]. Fertilisers are for basal and for topdressing. Fertilisers, including urea, have nutrient standards that ensure that the fertiliser will preserve or improve soil fertility and help the crops to grow. For example, in urea, the most important element is Nitrogen and samples of urea should contain 46% nitrogen. Tests were conducted by the International Institute of Tropical Agriculture and Sokoine University of Agriculture in 2016 in collaboration with researchers from the United States. The World Agroforestry Center Laboratory in Nairobi and Thornton Laboratory in the United States performed the testing. The shops did not know that the fertiliser purchased for testing was for a test and did not influence the results in any way. All the urea tested in from market [INSERT associated market name] in 2016 contained 46% Nitrogen. This means it met national and international product standards. The research found NO evidence of adulterated urea fertiliser. [Allow for questions from the attendees] We are here today to give you this important information and we have the pamphlets for you."

Following this transcript, pamphlets were also distributed to the farmers in attendance.

Figure A.4: Appendix Picture 1: Poster

Note: Translation: The fertilizer test was conducted by IITA and Sokoine University of Agriculture (SUA). All Urea samples tested in 2016 was found to have 46% Nitrogen. This means that Urea fertilizer met the international standards of quality. Urea fertilizer had a good quality.

Figure A.5: Appendix Picture 2: Pamphlet

Note: Translation: Researchers from Sokoine University of Agriculture (SUA) and the International Institute of Tropical Agriculture (IITA) in 2016 in collaboration with researchers from University of Illinois in the US tested the quality of fertiliser samples. The testing took place at the laboratories of World Agroforestry Centre (ICRAF) in Nairobi, Kenya and Thornton in the US. The agro dealers did not know that the fertiliser samples purchased for testing purpose, so they had no influence on the testing results. Fertilisers, including Urea, have nutrient standards that ensure that the fertiliser will preserve or improve soil fertility and help the crops to grow. For example, in urea, the most important element is Nitrogen and samples of urea should contain 46% nitrogen. All Urea samples taken in this village and tested in 2016 was found to have 46% Nitrogen. This means that Urea fertiliser met the international standards of quality. Urea fertiliser had a good quality. The results did not show any sign of Urea fertiliser adulteration.