Restoring Trust: Evidence from the fertiliser Market in Tanzania

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In markets for experience and credence goods, demand depends not only on prices and observable attributes, but also on trust in product quality. In low income countries, the government regulatory system is often weak, contributing to a lack of trust in critical production inputs. We implemented a randomized controlled trial in Tanzania to restore trust in fertiliser quality. While previous research has shown that fertiliser in Tanzania is of excellent quality, the majority of farmers have concerns. Fertiliser sellers and farmers in treatment market clusters received information explaining that urea fertiliser tested in their markets was good quality. The information treatment improves farmer beliefs about fertiliser quality and increases purchases and use. Sales in treated markets increased but prices remained stable.

Keywords: Fertiliser; Technology Adoption; Trust; Sub-Saharan Africa; Beliefs; Credence goods; Input quality

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1 Introduction

Markets do not function without trust. Markets with trust problems, where buyers have doubts about product quality, have higher transactions costs, as buyers must expend time and effort evaluating commodities (Stiglitz, 1989). In many transactions, particularly those involving goods with attributes that are unobservable at the time of purchase, buyers rely on beliefs about seller behaviour and product quality. When these beliefs are pessimistic, because of past experience, limited regulatory oversight, or information asymmetries, demand can collapse. A lack of trust is associated with lower economic growth and a lack of development (Zak and Knack, 2001; Dearmon and Grier, 2009; Algan and Cahuc, 2013).

Trust is central to the functioning of a range of markets, including expert services in healthcare and product repair (Dulleck and Kerschbamer, 2006), to the regulation of financial products (Van der Cruijsen, De Haan and Roerink, 2023), but also to the rise of online platforms and reputation mechanisms across many sectors (Miehe et al., 2023).

Trust problems related to product quality can be pervasive and acute in low-income countries, where government regulatory systems are often absent or minimally enforced. A lack of trust in product quality can reduce demand for a range of important goods in these countries, including health products (Björkman Nyqvist, Svensson and Yanagizawa-Drott, 2022; Adhvaryu, 2014), education (Jensen, 2010), insurance (Jensen and Barrett, 2017), and food (Bai, 2021). Furthermore, a lack of trust in product quality in one input can spill over into the demand for other inputs, reducing the use of complementary profit-enhancing technologies and inputs (Bulte et al., 2023).

Understanding how trust in markets breaks down, how it can be restored, and how it shapes outcomes is key to the study of market functioning. Dulleck and Kerschbamer (2006) develop a framework for credence goods in which private actors can resolve information asymmetries in the market for expert services if consumers are homogeneous, economies of scope exist, and some aspect of the technician's work is verifiable. Bai (2021), for example, finds that watermelon sellers in China (who have private information on the sweetness of particular melons) can build reputation, but only if the cost of doing so is sufficiently low, if credit is available to cover the cost, and consumers learn quickly.

In this paper we provide new evidence on these classic economic questions in the context of the fertiliser market in Tanzania — a market where a lack of trust helps explain persistently low rates of technology adoption, with direct implications for growth and poverty reduction.

Farmers in low-income 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. The agronomic quality of fertiliser is determined by its nutrient content; this 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). Other factors can also contribute. Farmers commonly apply the wrong fertilisers for their soil type and crops or may not time the application correctly (Rware et al., 2014; Harou et al., 2022). Many do not apply enough. For example, in our sample farmers who do apply fertiliser apply a mean of 53 kg per acre, around 48% of the agronomist recommended amount. This situation, combined with a lack of effective regulation, fuels suspicions among farmers. Michelson et al. (2021) document that farmers believe that agri-dealers tamper with the quality of fertilisers or allow them to degrade (see also Bold et al. (2017); Ashour et al. (2019); Sanabria, Dimithè and Alognikou (2013). These suspicions are in sharp contrast with the results of the fertiliser tests conducted in the same studies: testing the urea fertilisers from all agri-dealers in the region, Michelson et al. (2021) find that less than 1% of urea fertiliser samples tested had less than the required 46% nitrogen.[1] This result – that fertiliser is reliably good quality – is consistent with numerous other studies from the region (Sanabria, Dimithè and Alognikou, 2013; Sanabria et al., 2018*a*,*b*; Ashour et al., 2019; Michelson et al., 2023).

We test how a information campaign can restore trust in this critical market. We com-

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

bine a randomized controlled trial with detailed panel data on beliefs, purchases, and sales collected from a representative, large sample of farmers and from all shops within one agricultural region over the course of a year. This 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 randomly assigned all markets in Tanzania's Morogoro Region to either a treatment 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.[2] Retail shops selling fertilisers (henceforth agri-dealers) 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 farmers that the tested urea fertiliser quality was good. We collected data among these village farmers and all agri-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 and sequenced the work carefully.[3][4]

We find that farmers' concerns about fertiliser quality are considerable. At baseline, 77% of farmers report concerns about urea fertiliser quality, as measured by a probability-framed elicitation mechanism. The degree of these concerns correlate with previous experience with fertilisers. Farmers' concerns vary substantially by market, with farmers expressing fewer concerns about larger markets. These larger markets, which tend to be further away from the homestead, are also the markets where most farmers purchase fertilisers. Farmers' concerns change in response to the treatment, which reduces the probability of having any concern by 12%, and reduces the average level of concern by 30%. The treatment increases the

[2] We did not cross-randomize treatment assignment of markets and villages. Instead, the villages received the same treatment allocation as the nearby market.

[3] One year after our intervention, and after having established positive effects, we rolled out our intervention the control markets. See the ethics appendix.

[4] We partnered with Tanzania's Sokoine University of Agriculture (SUA), a local and well-trusted public university commonly engaged in extension activities in the region. 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.

probability of using urea fertiliser by 10 percentage points, an effect size of 27%. Fertiliser use per acre increased by 5.6 kg, an effect size of about 46%. New users are driving this effect, as they start to use fertiliser. We find no decrease in the use of non-urea fertilisers, suggesting that a simple redirection towards urea is not a mechanism in this case. We do note an increase in the use of hybrid maize seed, a well-known complementary investment.

Farmers who purchased fertiliser throughout our study redirect their purchases towards the nearby, local, smaller markets which were more distrusted at baseline. This indicates that the intervention does not (only) nudge farmers towards timely purchasing of fertilisers, as in Duflo, Kremer and Robinson (2011), but rather alters beliefs, and through these, behaviour. The effect on sales is also felt by the sellers. We find sizeable impacts on the quantity of urea sold, an effect size of almost 5%. We document no effects on market prices. Prices are regulated by the government, and as these regulations are largely adhered to, is not a relevant margin.

This paper makes three primary contributions. First, we show that a low-touch information campaign can meaningfully shift both beliefs on input quality and behaviour with regard to these inputs in a context where economic agents face severe liquidity and risk constraints, and where prior studies have found that information alone often has limited impact (Dercon et al., 2014; McIntosh, Sarris and Papadopoulos, 2013; Harou et al., 2022; Tamim et al., n.d.). This finding contributes to the growing literature on the effectiveness — and limits — of information interventions in smallholder agricultural markets (Hsu, 2020; Bai, 2021). Our evidence suggests that credibility of the information source, combined with the clear and immediate relevance to farmers' production decisions, may explain why this particular information campaign was successful.

Second, we show that incorrect beliefs about input quality directly reduce both demand for fertiliser and farmer experimentation with an important productivity-enhancing technology. This finding highlights the importance of misperceptions as a barrier to technology adoption, a mechanism that has been under-explored in the literature, relative to more widely studied constraints such as liquidity, risk, or learning costs (Boucher, Carter and Guirkinger, 2008; Karlan et al., 2014; Dercon and Christiaensen, 2011; Carter and Barrett, 2013; Cardell and Michelson, 2023; Minten, Koru and Stifel, 2013; Croppenstedt, Demeke and Meschi, 2003; Foster and Rosenzweig, 2010).[5] This confirms that fertiliser markets in regions characterized by limited regulation might not meet the conditions under which private actors can solve existing information gaps. Agri-dealers cannot build a reputation easily, as farmers, facing a stochastic production environment, cannot learn quickly enough about the quality of fertiliser from a given dealer, and the cost of third-party testing often exceeds the willingness-to-pay and credit access of the small-scale dealers (as among the grain sellers in Fuller and Ricker-Gilbert (2021) and Anissa et al. (2021)).

Third, we find that these incorrect beliefs may shape the structure of rural input markets. Farmers at baseline systematically distrust the smallest, most rural sellers, countering the conventional view that proximity and repeated interactions foster trust in low-information environments (Fafchamps, 2004; Mailath and Samuelson, 2006). Instead, farmers' distrust appears to be driven by observable market characteristics, such as limited competition, slow sales, and compromised product appearance due to longer storage and transport times (Michelson et al., 2021). This welfare-reducing equilibrium, in which farmers incur higher search and transport costs to purchase fertiliser in larger or more distant markets, underscores how incorrect beliefs can distort market structure in addition to reducing individual technology adoption. Our study adds to recent evidence that correcting misinformation about sellers and product quality can meaningfully increase market efficiency and welfare (Annan, 2022; Bai, 2021; Miehe et al., 2023; Gilligan and Karachiwalla, 2021; Hsu, 2020). Our study differs from recent contributions on the market for hybrid seeds. Hybrid seed quality can vary and sellers' actions can contribute to the quality (Michelson, Gourlay and Wollburg, 2022). Hence, a traditional lemons' market model applies (Akerlof, 1970, 1978). Interventions in this context suggest that some sellers are willing to improve quality and in-

[5]In Hoel et al. (2021) and Michelson et al. (2021) we show that farmer quality concerns lower their willingness-to-pay for fertilisers (relative to circumstances where the farmers are confident about quality).

vest in reputation, as long as farmers have means to verify relevant aspects of quality (Miehe et al., 2023; Gilligan and Karachiwalla, 2021; Hsu, 2020).

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 intervention. Section 5 explains the data sets: the farmer survey, the agri-dealer survey, and presents descriptive statistics for the samples. Section 6 presents analysis and results. Section 7 concludes.

2 Background

The market failure we address in this paper relates to consumers' lack of trust in the East African fertiliser market. This is a market characterized by unobservable product quality and limited regulatory enforcement.

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 agri-dealers, sell other agricultural inputs, and can also serve as informal credit-providers, information points, and buyers of agricultural output. All actors in this supply chain 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.[6] For example, in accordance with the Fertiliser Regulations Act, all dealers and premises must be registered and all fertiliser importers and exporters must acquire a special permit. Yet, only half of the agri-dealers in our sample are registered (see Table 4).

[6] 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 might increase costs for the sector because wholesalers and agri-dealers have to interact with and comply with several regulators.

Farmers in the region are aware of this lack of enforcement and suspect agri-dealers of tampering with the product (Michelson et al., 2021, 2023). These concerns are also reported by other studies in East Africa (Bold et al., 2017; Ashour et al., 2019; Sanabria, Dimithè and Alognikou, 2013).[7] Farmers' lack of trust should be viewed in a broader context of suspicion among citizens in the region. Tanzanians report low trust in their government, in their institutions, and in each other (generalised trust). For example, data from the Afrobarometer and the World Values Survey reveal that 46% of farmers reported that they were "never sure that vendors sell the correct amount of a kg of maize or rice to them".[8]

Farmers' widespread concerns regarding low quality fertiliser do not seem to reflect reality. In Michelson et al. (2021), conducted in 2015-16, we purchased urea fertiliser from all agri-dealers in Morogoro using mystery shoppers, and tested the fertiliser samples in laboratories in the United States and Kenya. We established that urea fertiliser quality was excellent across markets, with the required amount of nitrogen (46% nitrogen by weight). Less than 1% of urea fertiliser samples tested were missing nitrogen and then only trivially so, suggestive of manufacturing calibration issues. These results are consistent with other laboratory studies done in the area (Sanabria, Dimithè and Alognikou, 2013; Sanabria et al., 2018*a*,*b*; Ashour et al., 2019) and summarised in Michelson et al. (2023).[9]. In this study, 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 (see Table 4). Our goal is to assess the degree to which we can change farmer beliefs and, by changing beliefs, affect behaviour.

Fertiliser quality concerns are one among numerous constraints that farmers face in this region. Most cultivated land in Tanzania is characterized by low fertility, with nitrogen a primary limiting nutrient but other widespread nutrient deficiencies include phosphorus,

[7]These concerns can be reinforced in the media (Kasumini, 2016). Work by our research team in 2018 investigating the journalistic sources of several articles in the national newspaper 'The Citizen' found that the newspaper articles were themselves based on rumours rather than primary data collection.

[8]See also Sapienza, Toldra-Simats and Zingales (2013); Etang, Fielding and Knowles (2012); Glaeser et al. (2000).

[9]One study - Bold et al. (2017) - has reported extremely high and widespread nitrogen missing from urea fertiliser in Uganda. This study is an outlier in the literature and the scientific and economic implausibility of its results are discussed in Michelson et al. 2023

potassium and sulphur, copper, zinc, and magnesium (Marandu, Mbogoni and Ley, 2014). Farmers, however, lack knowledge about their soil (Harou et al., 2022; Corral et al., 2020). In addition, farmers often have limited access to credit (Boucher, Carter and Guirkinger, 2008) and insurance (Karlan et al., 2014; Dercon and Christiaensen, 2011; Carter and Barrett, 2013) and face significant yield and output market price risks (Cardell and Michelson, 2023; Minten, Koru and Stifel, 2013; Croppenstedt, Demeke and Meschi, 2003). A lack of access to post-harvest storage (Burke, Bergquist and Miguel, 2019) and governmental limits on fertiliser bag sizes (Simtowe, 2015) further complicate (inter-temporal) decision-making (Duflo, Kremer and Robinson, 2011).

Fertiliser use is low in Tanzania – significantly below recommended amounts (The World Bank, 2021). A large body of literature has established the high, albeit heterogeneous, marginal returns to increasing fertiliser use in the region.[10] The National Sample Census of Agriculture found that only 2.5 million hectares, which is 21.4% of total planted area, were cultivated with fertilisers in the 2019/2020 production season (National Bureau of Statistics, Tanzania, 2019). To compare, 40% of farmers in our baseline sample reported using fertiliser in the previous long rains growing season (see Table 3). Even for farmers who use fertiliser, application rates in Tanzania (and in Sub-Saharan Africa more broadly) are typically much lower than what is considered agronomically or economically optimal (Senkoro et al., 2017; Ariga et al., 2019). The Tanzanian government recommends use of 40.5 kg of nitrogen and 16 kg of phosphorous for one acre of maize cultivation, which implies application of 74 kg of urea and 35 kg of DAP per acre(Kohler, 2018).[11] Tanzania's per acre application rate is considerably below this number, estimated at 7 kilograms (The World Bank, 2021). In

[10] See, among others, 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); Sheahan and Barrett (2017); Chamberlin, Jayne and Snapp (2021).

[11] Recommendations are generally provided in terms of kilograms of nutrient per acre rather than per acre units of particular fertilisers, which are composed of different percentages of nutrients by weight. Urea for example is 46% nitrogen by weight. A 2018 Alliance for a Green Revolution for Africa (AGRA) report states: "The government recommendation is 100 kg N and 40 kg P_2O_5 per hectare, derived from either DAP or Triple superphosphate (TSP) at basal application and either urea or ammonium sulfate (SA) at topdress." These convert to 40.5 kg of N and 16 kg of phosphorous per acre.

our sample, farmers who used fertiliser in the last long rains growing season report using 34 kg per acre, about 30% of the recommended amount (generally a combination of urea and NPK).

This low use is notable given government policies in place aiming to encourage adoption and use. For example, the government subsidizes fertiliser through a system of price caps that vary regionally. While these regulations themselves have been in flux, price caps were in place during our survey period (in 2019-2020).[12] On the other hand, availability of fertiliser can be a concern. In 2019, a supply shock affected imports and widely restricted the availability of urea in the country the next growing season (in 2020) (United Republic of Tanzania, 2019). In addition, the regulations also prescribe bag sizes; for example, sales of 1 kg bags - which are generally scooped from open 50 kg bags - are prohibited.[13]

In early 2020, pre-election political changes resulted in the government being seen by the public as becoming more proactive in enforcing these fertiliser regulations regarding pricing, bag size and registration. The government's efforts were widely publicized in the local media, including crackdowns on unregistered fertiliser sellers.[14]

In our study, the government appears reasonably successful in enforcing these prices and, to a lesser extent, quantity regulations. The majority of agri-dealers adhered to the government-set maximum prices in 2020 (see Appendix Table A.13). Qualitative interviews we conducted with agri-dealers in 2020 concur. The dealers noted that they adhered to the government fertiliser pricing scheme, even though it results in small profit margins as the

[12] In 2017, Tanzania created the fertiliser Bulk Procurement System (FBPS), with the goal of reducing prices through government facilitation of imports (Bumb et al., 2021). Subsequent amendments to this regulation authorized the use of price caps on fertiliser sold: TFRA sets an indicative price for urea and DAP which is the maximum price at which fertiliser can be sold. This price varies by market location and by week (as the price accounts for transportation costs) and shops are required to display them in their shop windows. The Morogoro District Agricultural Extension and TFRA officers we interviewed noted that failure to adhere to these prices carries a three-year prison sentence or a fine of ten million Tanzanian shillings upon conviction. In 2021, the Minister of Agriculture announced the suspension of the fertiliser Bulk Procurement System, but then in 2022, following political turmoil, price caps were reinstated by the TFRA.

[13] The Fertiliser Act of 2009 as amended on February 2017, specified that the packaging for solid fertiliser must be in 5 kg, 10 kg, 25 kg, and 50 kg sizes; the TFRA may allow packages in weight less than 5 kg upon request.

[14] For example, RATIN `https://ratin.net/site/news_article/9593` and Africa Press `https://www.africa-press.net/tanzania/all-news/dealers-in-unregistered-fertilisers-to-be-penalised`.

mandated prices fail to sufficiently account for distance, weather, and wholesale prices. They also reported that the fertiliser package sizes available from wholesalers pose a problem. At the time of the survey, the smallest available official package was 5 kg, but often farmers want to purchase smaller sizes. All agri-dealers admitted to repacking fertiliser into 1 or 2 kg bags for sale or selling smaller quantities directly from open 25 or 50 kg bags. Even so, these small packs might not amount to much in terms of total share of sales. In our sample, in 2019, 70% of farmers who purchased urea, purchased in units of 50 kg bags.

In 2019, the Alliance for Green Revolution in Africa (AGRA) worked with TFRA to harmonize and centralize fertiliser policy with the aim of increasing trust in input quality (Keizire, Kapuya and Njoroge, 2020; United Republic of Tanzania, 2024). Our interviews conducted with Morogoro District Agricultural Extension and TFRA officers detail campaigns teaching farmers and agri-dealers to observe the expiration dates of the fertiliser at the point of sale, and increased enforcement of regulations related to the sale of sealed bags only. This increased perception of enforcement may be a key factor driving the overall improvement in quality concerns observed among our sample of farmers between 2019 and 2020 (see Section 6).

3 Sample and Randomization

3.1 Agri-dealers census and farmers sample

We selected the Morogoro Region as the study site. Smallholder agriculture accounts for 80-90% of the region's economic activity. Self-employment in agriculture provides the main income stream to households, and supports nearly all household activities. Most families consume what they grow and also sell some crops or livestock for income (Mutabazi et al., 2015).

We started in 2019 with the list of 100 markets identified in a census conducted in 2015/16 Michelson et al. (2021).[15] We conducted follow-up censuses of these markets at baseline in

[15] We define a market as a village location where there is at least one agri-dealer and one other businesses, including retail and wholesale shops, for farmers to purchase agricultural inputs and other consumables. A

early 2019 and once again at endline in early 2020, updating the lists to reflect all agri-dealers we found operating in the markets. In some we found no shops selling inputs. Our market census is therefore smaller than the 100 markets found in the 2015/16 census. The 2019 census (baseline) included 89 markets and the 2020 census (endline) included 85.

Table 1 provides an overview. Of the 430 agri-dealers surveyed at baseline (2019) and endline (2020), only 232 were interviewed in both rounds. As our data is a census of the agri-dealers operating in the markets in each round and as we were careful to visit during the same period of the year in each round - the input purchasing months when seasonal businesses would be in operation - these high entry and exit rates represent considerable market churning. Data collected at endline, and presented in Appendix Figure A.1, indicates that agri-dealer exit is mostly due to shops closing due to business failure, a dynamic further described and investigated in Naugler, Michelson and Janzen (2024).

The baseline data collection included the GPS location of each market. Figure 1 presents the market locations. We worked with government agricultural extension officers to locate all villages within a 3 to 7 km ring surrounding each 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. The 7 km upper boundary ensured that the link between the village and the market was meaningful, i.e., it would be feasible for the villagers to visit the market.

We randomly selected 148 villages from this 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 had 100 (initial) market locations, this implied that half of the markets had two matched villages while the other half had one matched village (this process was stratified by treatment/control status of the market, and randomized by market).[16] This means that some markets are linked with two villages, while others only one. We refer to these linked markets as the associated

village is as defined by the constitution of Tanzania as the lowest government administrative structure at the community level.

[16]As the rings of some markets overlapped, we randomized the sequence for this process. As a result, each village is only linked with one market in the data, despite 50% of villages situated near two markets or more.

markets.

The household sample consists of ten randomly selected farmers from a farmer census list for each village obtained from the government agricultural extension officers. We interviewed 1,479 households at baseline in 2019, and were able to reach 995 of these for an endline survey over the phone later in 2019. We conducted an in-person endline survey in 2020 in 29 villages and interviewed 220 farmers. Table 2 provides an overview.

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 for ethical reasons (refer to the ethics appendix for details). Each village was assigned a treatment status, with 74 villages (out of 148) in the treatment group and the remainder in the control 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 these markets.[17]

We emphasize that the treatment assignment of markets and villages was not cross-randomized. The design doubles down on the treatment. That is, 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 opted for it for several reasons. First, with only 100 markets in the region, baseline power calculations indicated that cross-randomization would likely be insufficient to detect effects on beliefs, purchasing, or usage. Second, the village treatment gains credibility among farmers: villagers

[17] 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. This was the case for 57 villages in the sample. In this case, we used a probability-based rule to assign status. 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.

informed about the intervention could visibly see the related posters in the market. Third, this non-selective strategy aligns well with typical policy implementation. Finally, the design helps to minimize spillover effects from treated markets to control villages.

4 Intervention

The goal of our intervention was to provide farmers and agri-dealers with the information we generated about fertiliser quality in our previous study (Michelson et al., 2021). Those results showed that the urea was excellent quality: 46% Nitrogen as required by international and regional standards.

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

The design required a separation of the intervention and data collection team. One team conducted the interviews, while another implemented the intervention, with the interviewing team always arriving and finishing their activities prior to the intervention team. This set-up also ensures that the beliefs we capture at baseline are genuinely before-intervention and not contaminated by any intervention activities. While we realize that best practices dictate that the intervention team and interview team are associated with two separate institutions (Gibson and Sautman, 2024; Islam, 2024), this was not feasible in our case. Sokoine University of Agriculture conducted the 2015/16 fertiliser sampling and market census and hence were best positioned to conduct the intervention. Farmers are familiar with the University, which has a neutral and expert reputation in the region.

We present the intervention timeline in Figure 2. Both village and market interventions were implemented in the two months between December 2018 and January 2019.[18] We present the intervention script and materials in the Appendix.

4.1 Market intervention

We began in the markets by informing the agri-dealers about the results of our prior research study using a standardized script explaining 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 presented this information, and whether we could leave a stack of pamphlets which the agri-dealer could distribute to their customers about the good quality urea rest results. To avoid strategic behaviour on the part of the agri-dealer, we also noted that we would be testing the fertiliser again in 2019.[19] None of the agri-dealers refused the posters or pamphlets. In each market, we provided each agri-dealer approximately two posters and 40 pamphlets to post or distribute as they saw fit.

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 shared a pamphlet with the individual making the inquiry. This happened quite often, as business continued as usual while we were in the shop.

4.2 Village intervention

We invited all farmers in the village to a public location, such as outside the village office. We informed the attendees about the results of the urea fertiliser quality tests we had

[18]We first completed the baseline interviews at the control markets, followed by the interviews and intervention at the treatment markets. Then, we completed the baseline interviews at the control villages, followed by the interviews and intervention at the treatment villages. The whole process lasted about one month. Hence, we are confident that our baseline surveys capture true baseline beliefs.

[19]We tested the urea fertiliser of 25 randomly selected agri-dealers in 2019, using mystery shoppers dressed in the style of local farmers to purchase the samples. The urea samples were shipped to the United States where they were tested at a university laboratory. All samples were of good quality, with between 45-46% nitrogen by weight.

conducted. 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 reported having attended our informational meeting (see Table 5). We focused the information session on tests conducted on fertiliser from the local, associated, market and we used a standardized script to relay this information. Recall that the village intervention linked up to the market intervention, with village treatments designed to reference and build on the local market intervention.[20]

At the end of 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 agri-dealers before and after the intervention. Enumerators visited farmers and agri-dealers in person at baseline. The endline farmer survey had two components: a phone survey in Fall 2019 among all farmers and an in-person survey in Spring 2020 in a sub-sample of villages (29 out of 148). Survey teams visited the agri-dealers in person in Spring 2020 for the endline survey (prior to the emergence of COVID-19). In addition, we conducted qualitative structured surveys among 40 randomly selected farmers and 20 agri-dealers throughout the study and interviews with the Morogoro District Agricultural Extension and TFRA officers. Figure 3 presents an overview.

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

5.1 Farmer survey

We interviewed the primary decision-maker responsible for the household's farm.[21] The same respondent was again interviewed in the phone and in-person endline survey in 99% and 96% of the cases, respectively. The respondent received a payment of 5000 TZS for the phone survey (about 2 USD at the time of the interview). The main results are based on the balanced panel comprised of the baseline and endline phone survey.The in-person endline data do not constitute a part of the main analysis.

We collected baseline data on respondent and farm characteristics: age, sex, education, risk aversion, and land ownership. At baseline and (phone) endline we collected farmer beliefs about fertiliser quality, and fertiliser purchases and use. A primary contribution of our project and data collection is the creation of a panel data set on fertiliser beliefs and fertiliser purchases. The in-person endline survey further asked about the sources of information, the perceptions of the village intervention and market intervention (which markets the respondent had visited in the past growing season and whether they had seen any of our posters there) and details related to maize production.

Beliefs about fertiliser quality To measure beliefs about fertiliser quality, we asked the farmer to consider three different markets, one at a time. We had pre-selected the three markets to include the three nearest markets to the village, one of which was the associated market (of the information intervention).[22] 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 then judge to be either of good quality or of bad quality (see

[21]We defined a household as individuals eating from the same kitchen on a daily basis for the last six months (excluding newborns).

[22]The pre-filled endline questionnaire contained errors among some farmers and presented them with duplicate markets. We did not use these data for the 28 farmers concerned as some respondents indicated conflicting responses with reference to the same market, possible referring to distinct purchasing experiences.

also Hoel et al. (2021) and Ashour et al. (2019) for a similar approach). Preceding this question, the enumerator discussed with the farmer that good quality related to the amount of nitrogen in urea (i.e., 46% by weight).[23]

Beliefs elicitation has become fairly common in 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 credibly elicit the beliefs regarding fertiliser quality during the baseline interviews and endline phone interviews. Note that we could not incentivize this question as by doing so, we would have had to reveal the truth about fertiliser to respondents in both treatment and control villages. To avoid knowledge from the interviewer spilling over to the respondent, something documented in other contexts as by Kerwin and Ordaz Reynoso (2021), we trained the enumerators to ask these questions in a neutral voice. Note that the over-the-phone elicitation is also less likely to result in these types of knowledge spillovers.

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 fertilisers: urea, NPK, DAP, minjingu fertiliser, CAN and SA (ammonium sulfate). At baseline (referencing the 2018 season), we asked the farmer how much of each fertiliser type the household had purchased, and where they purchased the fertiliser, allowing for multiple markets per fertiliser. If the respondent indicated that the household purchased fertiliser, we collected details about the cultivated acreage, the area fertilized, and the crops that received the fertiliser application. The endline phone survey inquired about fertiliser purchases during the previous (2019) long rains season, the price paid (per kilogram) and the (main) market where these purchases took place.

[23]The exact phrasing 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 which has 46% nitrogen."

Market visits At baseline, we asked the farmer about the markets he/she visited in the past twelve months prior to the interview. During the endline in-person survey, we asked the farmer whether they had visited any of the three nearest markets (with the option to add more markets if others were visited) in the last main agricultural season, 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 Agri-dealer survey

We aimed to interview the shop-owner in these interviews. If the shop-owner was not available, we interviewed another knowledgeable staff member. 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 recorded a series of in-person observations, detailing visible inventory, posted certifications, number of employees, and number of customers present.[24] In the endline survey, we collected data on stock facilities, current stocks and sales. We also inquired about the agri-dealer's perception of the market treatment, and repeated our in-person observations.

Sales: Quantities and Prices We focused on the same set of fertilisers with the agri-dealers as we had with the farmers: urea, NPK, DAP, minjinju, CAN and SA (ammonium sulfate). For each type, we recorded whether the dealer had ever sold the fertiliser, whether the dealer had some 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 some in stock). Due to concerns about the enforcement of the government's fertiliser maximum prices, prices were a sensitive topic. For this reason we avoided asking for prices at baseline, and only requested sales prices at endline, after having established a relationship with the dealer.

[24] We also collected information on business location, shop and ownership characteristics, assets ownership and asset rentals at endline for those businesses that we had not interviewed at baseline.

WTP for intervention In the endline survey we inquired about the agri-dealer's willingness-to-pay for a fertiliser quality certificate (by Sokoine University of Agriculture) similar to the information treatment provided in our intervention. We asked: "Imagine that Sokoine University of Agriculture 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?" While we did not use a Becker-DeGroot-Marschak 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. The 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 (IPA, 2022).[25] 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 29 villages. We use this survey to confirm participation and explore impacts on other inputs, rather than to establish main treatment effects.

Column (1) of Table 3 presents statistics for the full panel, Column (2) pertains to the control villages, and Column (3) to the treatment villages. Column (4) presents the p-value

[25] While our use of phone surveys was not driven by COVID-19-related concerns, we were aware of the many methodological studies conducted on phone surveys at that time, and followed recommended best practices, which included: setting up the baseline sampling and data collection (clustered, with phone numbers) to allow for follow-up with the phone, train enumerators, and facilitate reporting via pre-filled in excel files, and focused on few, easy-to-recall variables which overlap with other data sources to allow for data quality checks (see Gourlay et al. (2021); Brubaker, Kilic and Wollburg (2021); Wieser et al. (2010)). Despite these precautions, and the financial incentive, attrition is still substantial. We suspect two additional factors were at play. First, cellular phone reach was still limited in many areas of Tanzania in 2020, with no cell phone towers within miles of some villages. Second, at the time of our phone survey, the government of Tanzania had introduced a new regulation to require all phone owners to register their SIM card. This resulted in several households no longer owning phones or changing phone numbers.

of a t-statistic testing for differences between the means of the control and treatment villages. The majority of the respondents 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 (a regression of the treatment variable on all variables in Table 3 reports an R-square of 7%). We control for these baseline characteristics in our analysis.

The farmer sample can roughly be divided into three categories based on their recent fertiliser purchases: 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. Urea was the most commonly purchased fertiliser in the previous growing season (37% of farmers). Purchase and use of other fertilisers, including NPK, DAP, and CAN, are significantly less common. Slightly fewer farmers in the control villages purchased any fertiliser last season, and there is an imbalance in DAP purchases.

Conditional on purchasing fertiliser, 45% of all baseline farmers use it on all of their agricultural land, mostly applying urea to rice paddy (69% of farmers) or maize (53% of farmers), although 64% of farmers also apply urea to other crops. Application rates are far below the amounts recommended for this region (Kohler, 2018)[26].

Figure 4 presents the distribution of the kilograms of fertiliser used per acre of land among all baseline farmers (conditional on use and pooling across all fertiliser types). The mean is 34 kg per acre, around 31% of the government-recommended amounts. When considering only farmers who apply fertilisers to all of their land, the mean is 53 kg per acre, around 48% of the agronomist recommended amount. In addition to an insufficient amount, the literature has reported that farmers in this region often apply less effective fertiliser (for

[26] As noted earlier, the government recommends 40.5 kg per acre of nitrogen and 16 kg per acre of phosphorous for maize cultivation. Farmers can achieve this by applying some combination of urea (46% nitrogen by weight) and DAP or NPK. 74.43 kg of urea and 35 kg of DAP per acre is one means of achieving these recommendations.

their soil type and crops) and might not time the application optimally (Rware et al., 2014; Harou et al., 2022).

In Appendix Table A.2 we present the correlates of fertiliser purchases and use at baseline.[27] Baseline purchases of urea are associated with more land, while farmers who are more risk-loving are more likely to have purchased fertiliser. Farmers who purchased fertiliser also reported visiting more markets.

The farmers' exposure to markets might also affect the impact of the village intervention is successful, as some farmers will see the same information in the market. Over 70% of farmers visited one or two market locations in the year preceding the baseline data collection (this number has a range of 0-5), and for 41% this included the associated market. Recall that half of villages were close to more than one market, hence, it is possible that for some farmers it might not have been their most relevant market. Conditional on purchasing fertilisers, 85% of farmers purchase their fertilisers at just one market (with an average of 1.14 and range of 1-4). This implies that farmers visit markets for other reasons than just purchasing fertiliser. Recall that these local markets are hubs for various social and economic activities. Markets are visited to purchase larger consumer items, such as furniture, or specialty goods, such as children's toys, but also to attend events, and as a local transport hub. Baseline data indicates that most markets are visited yearly or monthly.

5.3.2 Agri-dealer statistics

Our main analysis sample consists of the balanced panel of agri-dealers present at both baseline and (in-person) endline interviews. Unlike the farmer sample, defining this analysis sample was challenging as agri-dealers moved, went out of business and started up during the project period. Attrition is substantial, 22% firms exited, primarily due to businesses closings and relocating (see Appendix Figure A.1). However, this attrition does not correlate with the market treatment (see Appendix Table A.4).

A more relevant concern might be firm entry, in particular, that the treatment itself might

[27] The reduced sample is due to missing observations in some of the control variables.

have encouraged market entrants. Appendix Figure A.2 presents a series of histograms, of the number of agri-dealers in a market, by market treatment and round. The treatment markets have more agri-dealers at baseline (this is also confirmed in Appendix Table A.6). This is due to the presence of several larger market hubs in the treatment group, like, Morogoro and Ifakara. Note however that the distributions do not change much between baseline and endline. A difference-in-difference regression confirms that the market intervention does not affect the number of agri-dealers in a market (see Appendix Table A.5). Overall, it appears that the treatment has not affected the market composition. This might be because fertiliser sales are often only a small share of the overall business, or because there are many other factors determining market entry/exit. Appendix Table A.3 provides an overview of the full sample. The analysis sample consists of 232 agri-dealers (out of a total of 430). As the data analysis requires baseline data, and we could not be sure of the extent to which new entrants were exposed to the treatment, ours represents a more conservative approach. In the analysis, we present a robustness check based on smaller sample, those agri-dealers selling fertilisers in both periods (the seventh category in Appendix Table A.3).

Table 4 presents descriptive statistics for the analysis sample in Column (1), Column (2) refers to the control market agri-dealers and Column (3) to the treatment market agri-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.

The majority of agri-dealers are male and have received secondary education or higher. 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 agri-dealer has been selling fertiliser is 4.2 years. Conditional on the shops being open, not all fertilisers are stocked and sold. Our baseline interviews took place in December and January, 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 agri-dealers had 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

Recall that to measure beliefs about urea fertiliser quality, we asked farmers to consider three different proximate markets, one at a time (including the associated market). We average the responses across the markets for each farmer to provide a measure of each farmer's belief. In the next sub-section, we exploit the considerable variation across markets (within farmers). On average, farmers expect three out of ten bags (of fertiliser) in their local markets to be of bad quality, and 77% of farmers have concerns regarding quality (see Table 3). We present the distribution in Figure 5: 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.

These fertiliser quality concerns are correlated with fertiliser experience. In Appendix Figure A.3 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.7 which maps farmer beliefs onto farmer characterizes at baseline.[28]

Village-level variation (that is, variation in beliefs within villages) appears substantial. There are no villages where everyone is unconcerned, but in 10% of villages, all farmers expressed concerns. These concerned villages are geographically concentrated in the northern

[28]The reduced sample is due to missing observations in some of the control variables.

area around Morogoro hills, a relatively remote area where farmers have little experience with fertilisers. Overall, this suggests that while experience with fertiliser can strengthen the farmers' confidence in fertiliser quality, this experimentation is often flawed as too little fertiliser is being used in sub-optimal manners. The lack of between-village correlation in beliefs suggests that social learning is limited as well (perhaps due to soil heterogeneity).

5.3.4 Descriptive analysis of market-level choice and beliefs

We further dis-aggregate this 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. That is, the same farmer will have different beliefs about the fertiliser quality across different markets.

Appendix Table A.8 presents the results of a series of farmer fixed effects market-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.[29]

While the results of these regressions need to be interpreted as correlations, we employ a farmer-fixed effect strategy to strengthen causality. Results show that farmers express fewer concerns for larger markets (Column (1)) - as captured by the number of agri-dealers present. Never having visited the market increases a farmer's concerns (Column (2)), while purchasing experience improves quality expectations (Column (3)). However, combining these factors into Column (4) results in a reduced coefficient size and a lack of statistical significance. This is due to multicollinearity between the independent variables. Inspecting correlations between these independent variables (and restricting the analysis to markets

[29]Note the smaller than expected sample size: While we endeavoured to include all farmers in this analysis, data quality limits our analysis as not all farmers were asked or provided beliefs estimates of the three markets. In about 10% of cases no market ID could be attributed to the listed market.

less than 50 km away due to a handful of sizeable outliers in the distance variable), we note that the larger markets tend to be further away from the homestead, and have less market churning (as measured by the ratio of agri-dealers selling in both rounds over all agri-dealer shops interviewed). Farmers are also more likely to visit and purchase at large markets.

These correlations imply that some farmers might be travelling quite far to purchase fertilisers. To investigate this proposition, in Appendix Table A.9, we present the results of a similar farmer fixed effects specification, this time with purchases at a given 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 almost 100 per farmer). So we included, for each farmer, the same three markets which were pre-selected by the research team as being closest to the village. Column (1) includes market-level characteristics. Column (2) adds information on visiting frequency (with observations where markets where never visited dropped for obvious reasons). Results in Column (1) suggest that farmers tend to purchase at those markets which have more permanent agri-dealers present, but everything else equal, also markets which are nearby (although this coefficient is small in size). Inclusion of the frequency of visits, in Column (2), reverses the results on distance (but remains very small in size) and maintains the core result on the importance of market size. Columns (3) and (4) present split the sample: farmers who purchased 50 kg urea or less are on the left, with farmers purchasing more than this on the right. This 50 kg is not only the sample median, but also the standard bag size in the area. We note that the results on distance are driven by the larger buyers: the larger buyers travel further away to purchase fertiliser.

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. Recall that 7 in 10 farmers had concerns about the quality of fertiliser at baseline. Given the nature of our intervention, change in beliefs is the main mechanism driving possible change in fertiliser use given we made no changes to prices or to access to financial resources, for example.[30] Our information intervention was well received by the farmers. Table 5 provides an overview of farmers' perception of the intervention from the in-person endline survey. The meetings were attended by almost all farmers (94%); 96% of those who attended reported that the meetings were useful. Farmers reported that information presented by the research team in the meetings was both useful (by 67%) and surprising (by 57%).

We define two dependent variables: the average (across markets) number of bad bags (out of ten) and the binary version of this measure, 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 (representing late 2019) and *base* refers to the baseline round (representing 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 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 6 presents the results of specification (1). The effects reported are statistically significant and sizeable. The treatment 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%.

[30] 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 and submitted to the main funder, PEDL. In the ethics appendix we further detail the structure and use of this plan.

Figure 6 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 groups at baseline. The distribution changes between base and endline in both groups, although more so in the treatment villages. Note that not all farmers in the treatment group were convinced by the information treatment, with over 50% still having concerns post intervention. Farmers in the control group report decreased concerns as well. While spillovers might have played some role (and hence the effects estimated in Table 6 should be viewed as a lower bound), recall that at the time of the survey a widely-publicized government crackdown on non-registered agri-dealers might have resulted in a reduction in concern across treatment and control groups.

The potential of information to spread beyond the borders of treated villages and markets implies that spillovers might be important in this context. We investigate the degree to which information may have spread beyond the intended recipients, between villages, between markets, and from treated markets to villages. First, the between-village spillovers are limited, most likely due to the geographic isolation of the villages. In the endline in-person 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 (see Rows (5) and (6) in Table 5). This interpretation is confirmed in Appendix Table A.10 as the distance to the nearest treatment village does not correlate with the endline beliefs of farmers in the control villages (see Columns (1) and (2)). Second, the between-market spillovers are limited, most likely because it is not in the agri-dealer's interest to share the information posters and pamphlets with other dealers. Only 18% of agri-dealers reported having shared them with others. Furthermore, the shared posters do not appear to have ended up at the control markets. From the agri-dealer endline survey (considering all endline dealers) we know that only 21% of agri-dealers in the control markets had seen the posters or pamphlets, and among those, 65% had seen them in other markets.

A more significant concern is the potential 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, and some farmers in control villages might have visited treatment markets during the duration of our study. Indeed, 38% of farmers in control villages, interviewed in person at endline, reported having seen the posters (versus 65% of farmers in the treatment villages, see Rows (7) and (8) in Table 5. In Appendix Table A.11 we correlate beliefs to measures of baseline exposure (to the treatment markets) among control farmers. The distance to a treatment market does not correlate with the farmers' endline beliefs in the control villages (this is also confirmed in Table A.10). There is a negative (and almost statistical significant) relationship between whether a farmer had visited a treatment market at baseline and endline beliefs. If the associated market is a treatment market (which did happen in 17% of this sample, as recall, in the case that villages are close to markets of a different treatment status, a randomization routine was applied), farmers report that they are 12 percentage points less concerned. It is notable that the effect size is similar to Column (2) in Table 6. While this appears to suggest that a market intervention might be equally effective compared to a village plus market intervention, caution is required as this is a sub-sample of villages which are close to several market centres.

6.2 Effect on farmer purchases

We investigate the effects of the village treatment on fertiliser purchases 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 capturing 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. $INFO$ refers to the village treatment and = 1 if the village was a treatment village, and = 0 if the village was a control village. The variable $AFTER$ refers to the data collection round and = 1 if this was the endline, referring to the 2019 main growing season, or = 0 if this was the baseline, referring to the 2018 main growing season. Baseline control variables X 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:

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

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

Note that in the specifications above, we treat fertiliser purchase quantities and fertiliser application quantities as equivalent. Qualitative interviews preceding the baseline established that the farmers in this region generally do not store fertiliser across seasons (as this is expensive and also because they worry about quality deteriorating over time) nor do they purchase fertiliser to resell to others.

Table 7 presents the effects of the village treatment on fertiliser purchases following specification (2). 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)). Note also the negative estimate on the after variable, indicating that urea use decreased over time. This might be due to the supply shock which affected imports and restricted the fertiliser supply in the 2019 year.

In Appendix Table A.12 we present the effects on other fertilisers. We do not observe any meaningful effects (there is a significant but economically small negative coefficient on SA (ammonium sulfate) fertiliser) suggesting the information treatment which focused on urea did not affect the use of other fertilisers (or that we are under powered to detect any such spillover effect, if present). The lack of negative impacts suggests that a possible alternative mechanism, in which we view the treatment to result in a simplification of the decision-making process of farmers and redirect them towards urea, instead of, for example, DAP - is unlikely to be the main driving force.

The discrepancy between Columns (1) and (2) in Table 7 suggests that new users might be driving the overall effect. To explore this point, we present a split-sample analysis in Table 7. Column (3) present the results for those farmers who previously used fertiliser, and Column (4) refer to those farmers who never used fertiliser before. We note a sizeable statistically significant increase in urea use among the second group of farmers. To gain a better sense of how meaningful this increase is among these new users, we present in Table 8 the effect on fertiliser use per cultivated acre (using specification (3)). This includes all fertiliser types, including urea. In contrast with the results in Column (2) in Table 7, we note an overall increase in the per-acre usage, by 5.64 kg per acre, which corresponds to an effect size of 46%. Splitting the sample, we find that the treatment increases use among prior non-users by 2.43 kg per acre. This increase might appear modest (compared to the 74 kg/acre urea recommended by agronomists), but still includes a significant number of farmers who do not use fertiliser. On average, new users apply 20 kg of urea per acre at endline, which is 27% of the recommended amount of 74 kg per acre (of urea). While we do not know for certain whether this implies that the farmer spreads fertiliser too thin, we do know that incorrectly applied the expected yield will not be be achieved, and dis-adoption may follow.

The bag size distribution (as far as we can deduct this from the purchasing data) is quite different among these new users. While 70% of all users at baseline purchased 50 kg or multiples of 50 kg (which would suggest they purchased the standard bag size), among the new users, 54% purchased 50 kg or multiples of 50 kg. The use of small bags was much more common among these new users, with 25% using 1 and 5 kg bags. Recall that the minimum package size allowed by government regulation was 5 kg at the time of our survey, but most dealers would not have this size in stock, and instead, if farmers asked for an amount below 50 kg, would have scooped the requested amount from an open bag.

6.3 Effects on farmer inputs and outputs

In this subsection, we document effects on other farmer investment or outcome variables. The regressions are based on a much smaller sample, using endline data from the in-person survey.[31] As many of these variables were not recorded at baseline, we use a specification similar to specification (3) in Table 9. Column (1) considers effects on cultivated maize acreage, Columns (2) and (3) on use of agro-chemicals and hybrid seeds, respectively, 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 at the 10% level), 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 agri-dealers might translate into more trust in the quality of the hybrid seeds (as suggested by Ariga et al. (2019)). 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, 64% of baseline farmers who used urea applied it to other crops as well. This implies that

[31] 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. However, the control villages within this sample start off with significantly worse beliefs in terms of fertiliser quality; and this being the main mechanism, might imply that we might be over-estimating the treatment effect in this table (although we do control for baseline beliefs in Table 9). Attrition is also significant, at 27%. This is partially due to the fact that one village was not reached at all (we had intended for a sample of 30, not 29). Attrition is not correlated with the village treatment status. See Appendix Table A.1.

effects on yield might have been visible to farmers on those crops instead.

6.4 Effect on agri-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 of urea and DAP are controlled by the government and agri-dealers are concerned about enforcement, we hypothesized that there was unlikely to be much effect on urea prices.

To test for price effects at the agri-dealer level, we begin this section by estimating specification (4) (recognizing we have endline data only). We restrict our sample to the balanced panel, i.e. those agri-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 $INFO$ 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 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. We cluster standard errors at the market level.

Table 10 presents the results. In Column (1), we note no statistical significant impact on the price of urea sold (the sample is further restricted to those businesses which reported prices). This is consistent with our hypothesis. We like to emphasize that even though pricing might be a sensitive topic, we have confidence in the quality of these data. To back-up this point, Appendix Figure A.4 presents kernel densities of urea prices for dealers which had urea in stock and dealers which did not have urea in stock. One notes an close mapping of both distributions, indicating that most dealers are aware off and reported the going market price. Appendix Table A.13 further compares the dealer-reported prices with the prices farmers report having paid for during the 2019 season (per kg). While they refer to a slightly different period and unit, they are similar in magnitude.

Furthermore, the going market price is close to the government set maximum prices: 52% of reported urea prices are within 15% of the government price of February 2020 (see Appendix Table A.13), consistent with the results of the qualitative interviews where agri-dealers noted to adhere to these regulations.[32][33]

In Column (2) of Table 10 we note a significant effect on the WTP. To interpret the significance of this effect, 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 sizeable coefficient, 35,349 TS (around 14 USD), representing an effect size of about 70% (although the p-value is 0.2). 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 47,950 (about 20 USD).

To investigate the effects on sales, we alter our specification, taking advantage of the panel data. Denote the agri-dealer by subscript j, the market by m, and the round by t. We use difference-in-difference specification (5) as 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.[34]

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

[32] Recall that government prices is a price per month per location, so these statistics do not imply that the remaining 48% does not adhere to government prices. Regressing urea prices using a market fixed effects regression one can explain 60% of the variation (with slightly lower average prices in larger markets).

[33] As a robustness check, we repeat Table 10 using the farmer-reported prices (at endline, referring to the 2019 season) in Appendix table A.14. Note that samples are small and vary across the columns because the observation is only included conditional on the farmer having purchased the fertiliser.

[34] 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.

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. $INFO$ refers to the market treatment and = 1 if the market was treated, and = 0 if the market was a control market. The variable $AFTER$ refers to the data collection round and = 1 if this was the endline, referring to the 2019 year, or = 0 if this was the baseline, referring to the 2018 year. We test the hypotheses $\beta_1 = 0$. The control variables X 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 11 presents the results of Specification (5). Columns (1) through (3) refer to the balanced sample, while Columns (4) and (5) trim the sample to include only those agri-dealers who sold fertilisers in both periods (after checking that the sample maintains its balance). We again note a negative year effect in Column (2), capturing the supply constraints in the 2019 calendar year. We detect no statistically significant effects of the treatment on the extensive margin in Column (1). Nor do we note any statistically significant effects in the intensive margin, on sales of urea or fertilisers as a whole.

One of the reasons of the overall lack of effects might be that sales is not normally distributed, but tends to have a long right-tail. In Appendix Figure A.5 we plot the kernel density of the quantity of urea sold at endline in 2019 (capped at 50,000 kg/year). The treatment group distribution has a significantly longer tail than the control group. This is partially due to the fact that the treatment group has some of the largest markets in the region which also have above-average sized sellers. But it might also be indicative of possible effects among a sub-set of agri-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)).[35]

We present the estimation results of an alternative model, a Bayesian hierarchical model, an addition which was not included in the pre-analysis plan. We use the R-package developed by Meredith and Kruschke (2021) (including their conservative priors which are close to zero) and build on Tushi et al. (2023) to estimate the average treatment effects of the market treatment on the various sales variables. Table 12 presents the results of 100,000 draws from the posterior distribution of the average treatment effect. We focus our discussion on rows (2) and (3), which present the analysis for the continuous variables for the analysis sample. 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%. We note no impacts on the total amount of fertiliser sold.

6.5 Changes in farmer purchases across markets

In this subsection we 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.[36]

Appendix Table A.15 presents the results. Columns (1) and (2) use the in-person endline data to establish the treatment 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. Columns (3) through (6) use the endline phone

[35] Splitting the analysis in Table 11 by market size, we note statistically significant impact on urea and overall sales among agri-dealers in markets with more than 5 agri-dealers at baseline (which is the medium market size).

[36] At baseline we asked the farmer to list all markets visited in the past 12 months. During the endline in-person survey, we proposed the three pre-selected markets, and allowed farmers to add more to this list, and referenced the previous long rains season. During the endline phone survey, the enumerators inquired about the main market for each fertiliser type purchased, while at baseline multiple markets could be mentioned. Finally, farmers were allowed to mention markets by name, and those observations where no ID could be assigned were dropped in this analysis.

data to establish correlations between the treatment and market purchasing behaviour. The sample in Columns (3) through (6) is limited to those farmers who purchased fertiliser in both years (and for those farmers where we had market IDs). Hence, the results presented in these columns should be viewed as correlations. 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 dependent variable in Column (4) is whether the farmer made a purchase at a market with 5 or fewer agri-dealers (recall this is the median market size), and Column (6) indicates whether the farmer switched markets. We find farmers are more likely to use the local, associated market, and purchase fertiliser closer to home. This should be seen against a backdrop of a move towards purchasing in larger markets, which tend to be further away: the baseline distance is 25 km, while the endline distance is 27 km, and the percentage of farmers purchasing at a small market is 45% at baseline and 40% at endline. As the information intervention centred around the associated market, which was the nearest market, this implies that our treatment may have helped build trust in these local markets, convincing the farmer to continue to purchase at their local market (Column (6) is almost statistically significant at the 10% level). These results, which are based on the sample of farmers whom purchase fertiliser in both periods, also indicate that an alternative channel, where the treatment, through extension-led discussions, simply nudges the farmers to purchase fertiliser in a timely fashion time, as in Duflo, Kremer and Robinson (2011), cannot be the only factor, as farmers appear to respond to the market-specific information.

7 Conclusion

We implemented a randomized controlled trial in Tanzania to test the effects of an information campaign about urea fertiliser quality. The goal of this campaign was to correct farmer beliefs about fertiliser quality. Previous research has established that farmers in the region distrust fertiliser sellers, and limited learning opportunities has entrenched this distrust. We distributed pamphlets and posters in randomly selected markets and villages.

These materials conveyed the message that all urea tested in the region was found to be good quality. The study worked at scale, and incorporated all markets and all agri-dealers in Morogoro region, as well as farmers from 148 surrounding villages.

The information treatment significantly improved farmer beliefs about fertiliser quality six months after the intervention, by 30% (from 3 to 2.4 bad quality bags out of ten as a measure). Treatment increased the likelihood that a farmer purchases urea fertiliser by 27%. The intervention, which centred around urea, the most commonly used fertiliser, did not reduce the use of other fertilisers, like, DAP. New users applied 27% of the agronomist-recommended amounts, and commonly purchased urea in smaller 1 to 5 kg bags. 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 urea prices, as expected in this price-regulated market, but note an increase in the use of hybrid maize, a well-known fertiliser complement.

These represent sizeable effects for a low-touch information campaign, especially one that provided no other services or subventions for purchasing. We conclude with some reflection as to how "low-touch" one might be able to go. In this study, the information campaign was implemented at two levels simultaneously, the markets and the villages. The village level intervention involved in-person meetings with agricultural extension officers and increased the cost substantially (that is, if the campaign is not integrated in an existing extension schedule). While a spillover analysis suggests that a market-level intervention might also improve beliefs, this result might be driven by the unique nature of control villages which are near several markets. In effect, splitting up of the two interventions might have unintended consequences, and needs to be considered within a framework of trust building, and in particular, a clear view of the level at which trust breaks down.

Do farmers believe the quality of all inputs is poor due to upstream issues, for example, due to corruption, delays and mishandling among wholesalers or 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 attributable to other actions taken by opportunistic dealers? Our market-level analysis suggest that the latter two factors are more important. Farmers do not believe the issues with quality stem from upstream sources. Instead, the results are consistent with concerns regarding transportation and a lack of competition in mostly local, smaller markets.

Another aspect to be considered when decoupling an information intervention is that the way information is presented contributes to its trustworthiness. The village information intervention was led by a trustworthy party, a local public research university in collaboration with government extension officers. This ensured that the presentation was consistent in execution with the kinds of village presentations that are frequently used in regional extension. Farmers would then receive the same information from sellers at their local market. This design, the collaboration of university researchers with government officials and sellers, provides an avenue to scale, fund and sustain the project longer-term. The integration of government officials not only ensured they too became aware of the mismatch between beliefs and reality, but that they had a framework in place to proceed with the work the research team had started.

This paper demonstrates that incorrect beliefs about fertiliser quality constrain farmers' demand in Tanzania. Although fertiliser is a crucial input for agricultural production, only one-fifth of the total planted area in Tanzania was cultivated with fertiliser (National Bureau of Statistics, Tanzania, 2019). Policymakers have largely relied on subsidies to address this low adoption (Jayne and Rashid, 2013). However, the findings of this study suggest that the effectiveness of these programs may also depend on the information environment of both farmers and agri-dealers.

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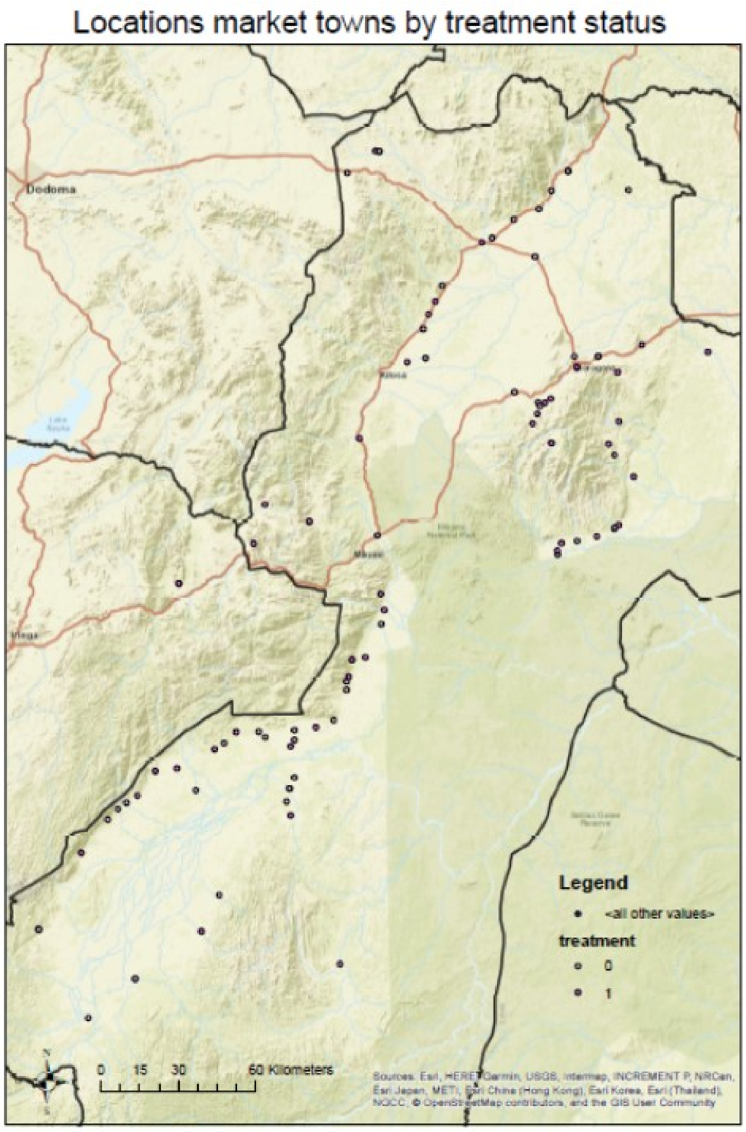
Figures and Tables

Figure 1: Study area map - market locations



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

Figure 2: Study intervention timeline (December 2018 – January 2019)

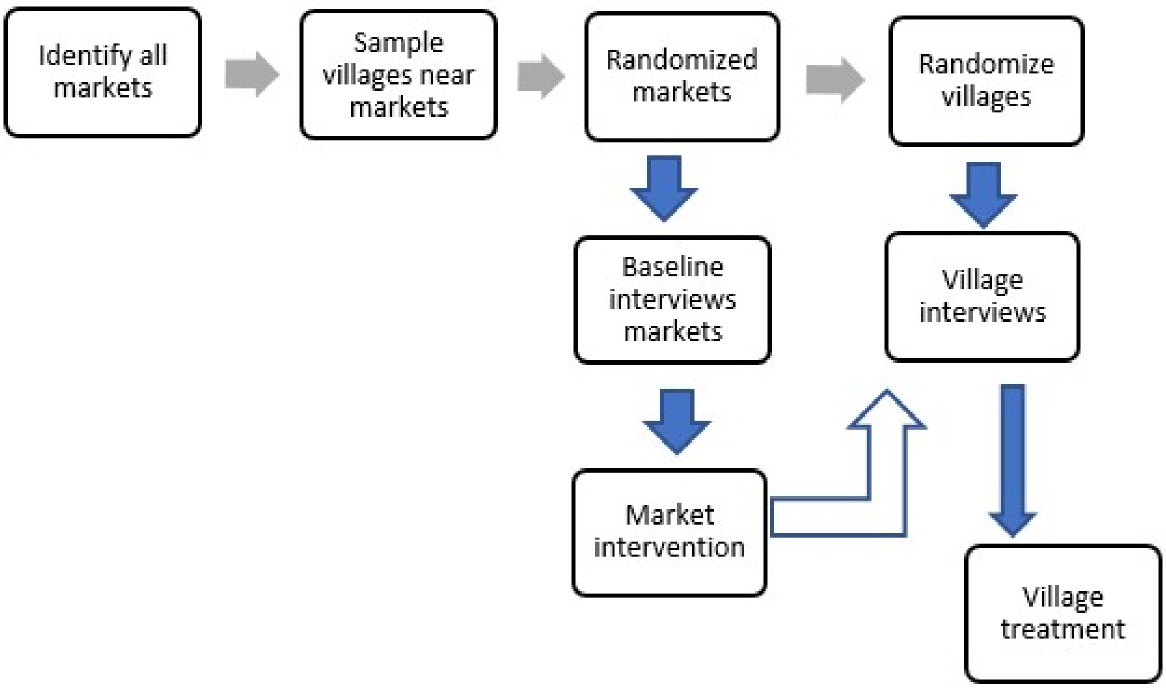


Figure 3: Data collection

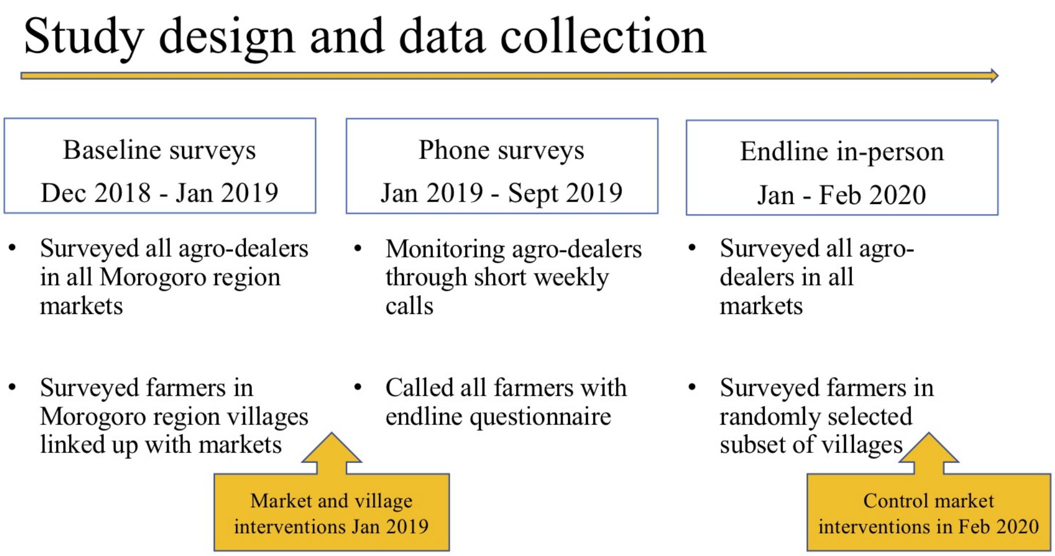


Figure 4: Kg fertiliser per acre cultivated, conditional on having purchased fertiliser, at baseline (balanced panel)

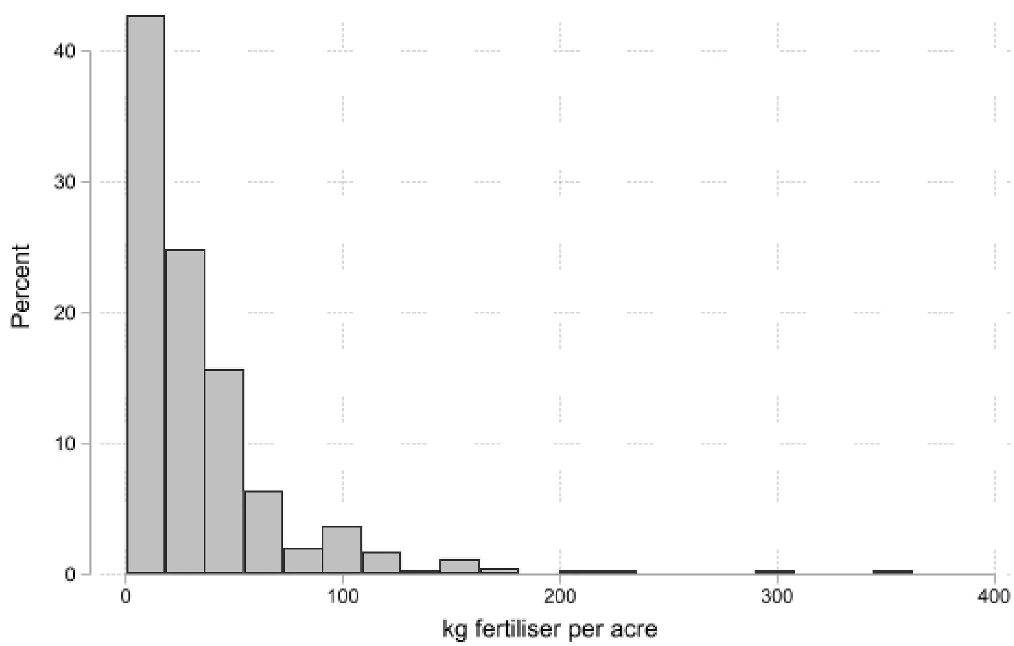


Figure 5: Distribution of the beliefs regarding fertiliser quality at baseline, in bad quality bags out of ten (balanced panel)

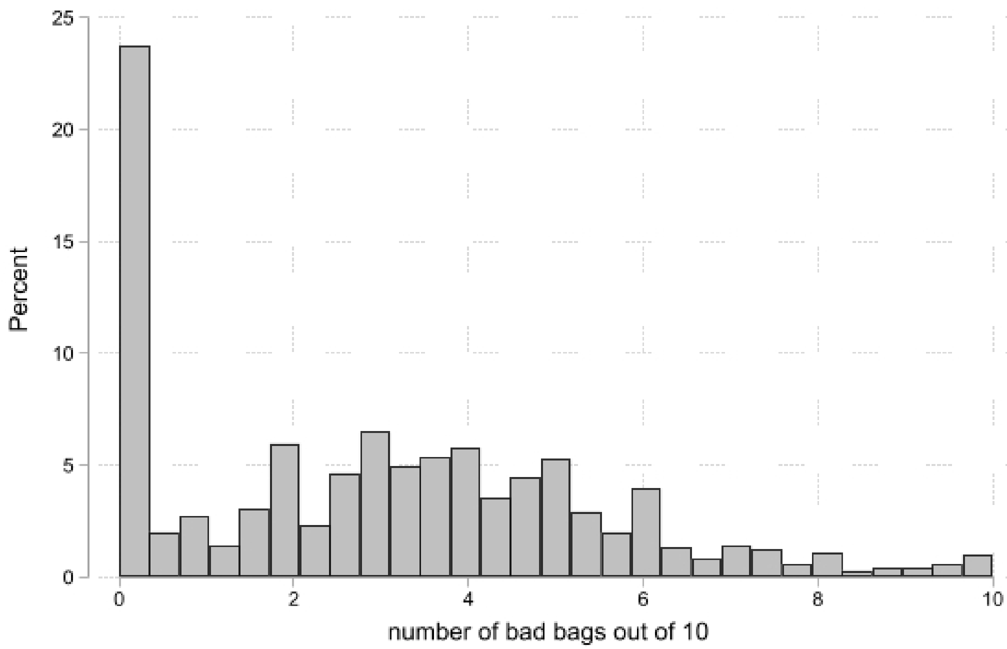


Figure 6: Histogram of beliefs regarding fertiliser quality (average number of bad quality bags out of ten), by round and by village treatment (balanced panel)

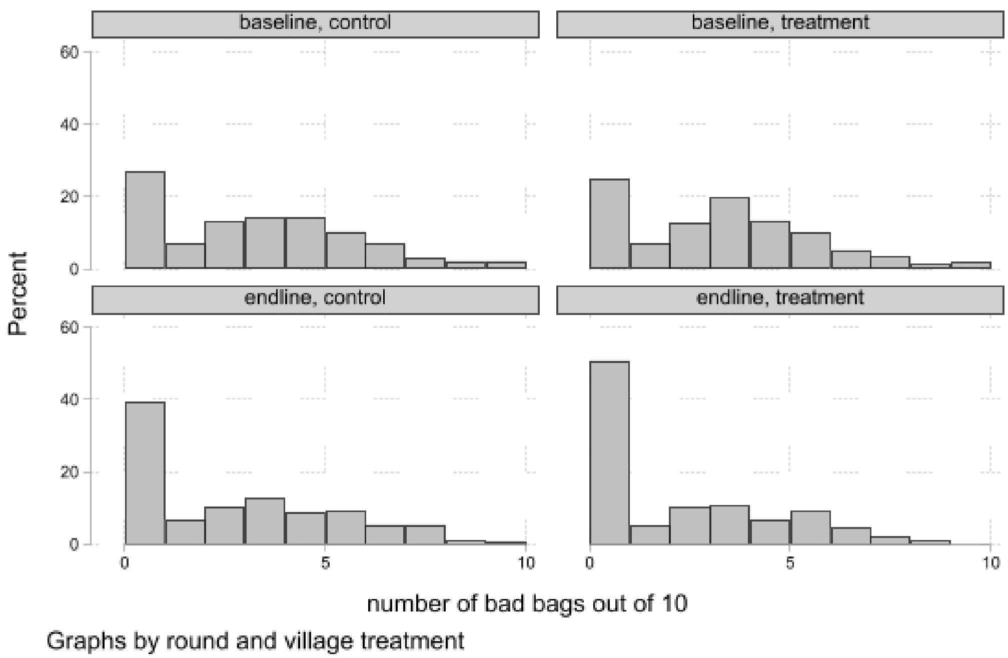


Table 1: Number of agro-dealers interviewed at base and endline

	Interviewed at baseline	Not interviewed at baseline
Interviewed at endline	232	132
Not interviewed at endline	66	NA

Table 2: Number of farmers interviewed at base and endline

	Interviewed at baseline	Not interviewed at baseline
Interviewed at phone endline	995	NA
Not interviewed at phone endline	484	NA
Interviewed at in person endline	220	NA
Not interviewed at in person endline	1,259	NA

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

Variable	(1) All villages	(2) Control Villages	(3) Treatment villages	(4) p-value
Sex respondent (1 = female ; 0 = male)	0.40 (0.49)	0.42 (0.49)	0.38 (0.49)	0.19
Age respondent (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 fertilizer (1 = yes ; 0 = no)	0.59 (0.49)	0.58 (0.49)	0.61 (0.49)	0.35
fertilizer purchased in previous growing season (1 = yes ; 0 = no)	0.40 (0.49)	0.38 (0.48)	0.43 (0.49)	0.08*
Urea purchased in previous 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 (if none = 0)	41.68 (146.14)	41.34 (174.13)	42.02 (111.59)	0.94
NPK purchased in previous 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 (if none = 0)	1.78 (25.72)	1.06 (9.49)	2.45 (35.10)	0.38
DAP purchased in previous 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) previous growing season (if none = 0)	9.70 (70.71)	11.58 (86.48)	7.84 (50.30)	0.40
CAN purchased in previous 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) previous growing season (if none = 0)	4.58 (37.72)	2.65 (14.68)	6.51 (51.22)	0.10*
Number of bad quality bags of fertilizer (out of ten)	3.04 (2.42)	3.08 (0.11)	3.05 (0.10)	0.55
Any concern about fertilizer quality (1 = yes ; 0 = no)	0.77 (0.41)	0.77 (0.42)	0.78 (0.41)	0.49
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 fertilizer***	1.14 (0.39)	1.16 (0.44)	1.12 (0.35)	0.27
Visited associated market in the past 12 months (yes=1; no=0)	0.41 (0.49)	0.41 (0.49)	0.41 (0.49)	0.91
Purchased fertilizer at associated market (yes=1; no=0)***	0.40 (0.49)	0.41 (0.49)	0.39 (0.49)	0.80

Note: This table presents the results of a baseline balance test for the farmers. Column (1) presents the average and standard deviation of the full analysis sample, Column (2) of the control villages and 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 the endline phone 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.*** This refers to the previous 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 for the agro-dealers. 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 fertiliser 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: Farmers self-reported usefulness of the village intervention

	Question in endline survey	Percentage of treatment farmers	N
(1)	Attended the in person meeting	94	109
(2)	Stated to be very to somewhat surprised by information shared at meeting	57	102
(3)	Found the information shared very credible	67	102
(4)	Found the information shared useful to very useful	96	102
(5)	Shared the information with others	94	
(6)	Shared the information with farmers outside of the village	23	102
	Question in in person endline survey	Percentage of farmers	
(7)	Saw market posters (treatment village farmers)	65	109
(8)	Saw market posters (control village farmers)	38	111

Note: This table present descriptive statistics pertaining to the in-person endline farmer survey. Rows (2) through (6) are conditional on attending the village intervention meeting.

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

Variable	Number of bad quality bags (out of ten)	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
Baseline mean	3.04	0.77

Note: This table presents the results of an OLS regression following ANCOVA Specification (1) using the farmer 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 7: The effects of the village intervention on fertiliser purchases of farmers

Variable	(1) Full sample Urea (0/1)	(2) Full sample Urea (kg)	(3) Used fertiliser before Urea (kg)	(4) Did not use fertiliser before Urea (kg)
Village intervention * After	0.106***	8.532	11.03	6.120*
	(0.0333)	(8.239)	(13.26)	(3.241)
After	-0.0512**	-9.158	-17.83*	2.922**
	(0.0258)	(5.694)	(9.561)	(1.274)
Village intervention	0.0382	4.063	7.672	0.454
	(0.0476)	(10.97)	(15.87)	(0.449)
Baseline controls	Yes	Yes	Yes	Yes
Observations	1,956	1,956	1,166	790
R-squared	0.121	0.096	0.123	0.050

Note: This table presents the results of an OLS regression following the difference-in-difference Specification (2). 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) present the results for those farmers who used fertiliser before and Column (4) 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 fertiliser use of farmers (kg/acre)

Variable	(1) Full sample	(2) Used fertilizer before	(3) Did not use fertilizer before
Village intervention	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. The mean of the dependent variable refers to the mean at endline. 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 endline phone 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 9: 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 farmers sample between base 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 10: The effects of the market intervention on agro-dealer prices

	(1)	(2)
Variable	Urea price (TZS/50 kg)	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 agro-dealers 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 license, 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

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

Note: This table presents the results of an OLS regression following difference-in-difference Specification 5. The sample is the balanced panel in Columns (1) through (3). Columns (4) and (5) limit the sample further to those agro-dealers who sell fertilisers in both periods. Columns (2) and (4) include those agro-dealers who have ever sold urea. Control variables include: Sex owner, education owner, age owner, TFRA license, 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.

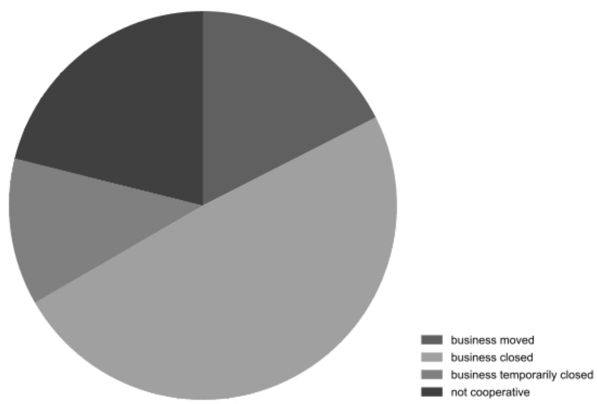
Table 12: The effects of the market intervention on agro-dealer sales: Mean Bayesian posterior distribution of treatment effects

Variable	(1) Avg. Treatment Effect (μ1 - μ2)	(2) HDIlo	(3) HDIhigh	(4) Prob (< 0)	(5) Prob (0 >)
(1) Urea in stock (1 = yes; 0 = no)	-0.0287	-0.121	0.0671	72.6%	27.4%
(2) Quantity urea sold (kg/year)	452	-226	1120	9.2%	90.8%
(3) Fertilizer sold (kg/year)	-205	-870	458	73.0%	27.0%

Note: This table presents the results of a Bayesian hierarchical model. The sample is the balanced panel. 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.

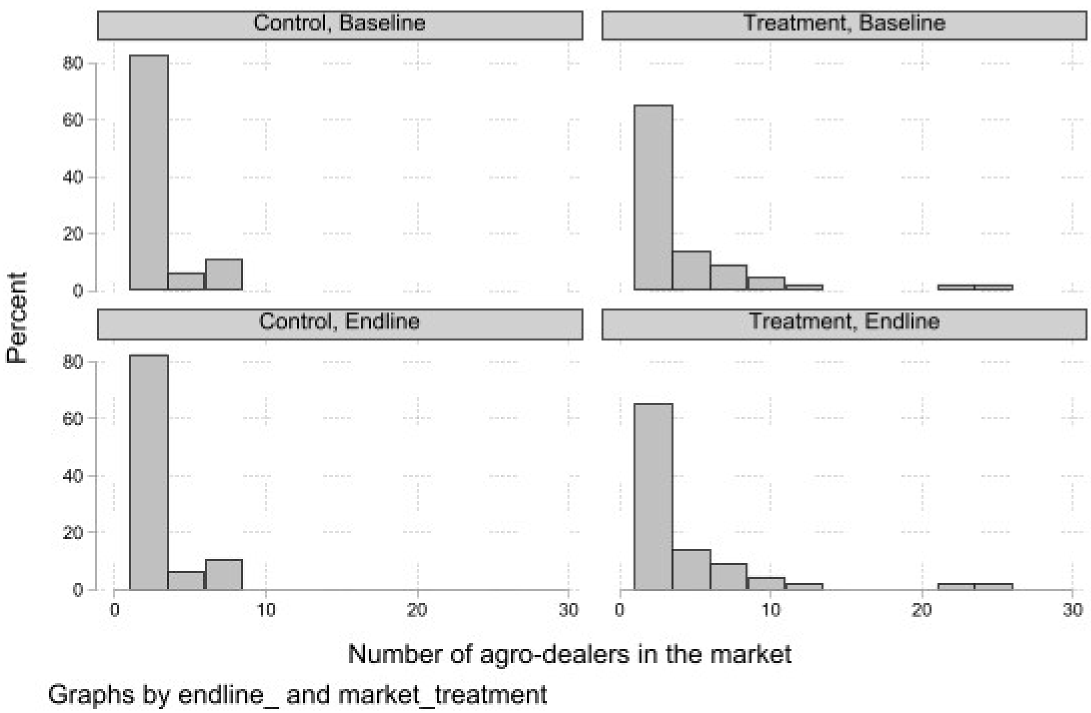
Data Appendix

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: Agro-dealer sample



Note: Histogram of the number of agro-dealers by round and by market treatment.

Figure A.3: Histograms of farmer-reported beliefs about fertiliser quality presented by whether the farmer had ever purchased fertiliser previously (bad quality bags out of ten). Balanced panel (analysis sample).

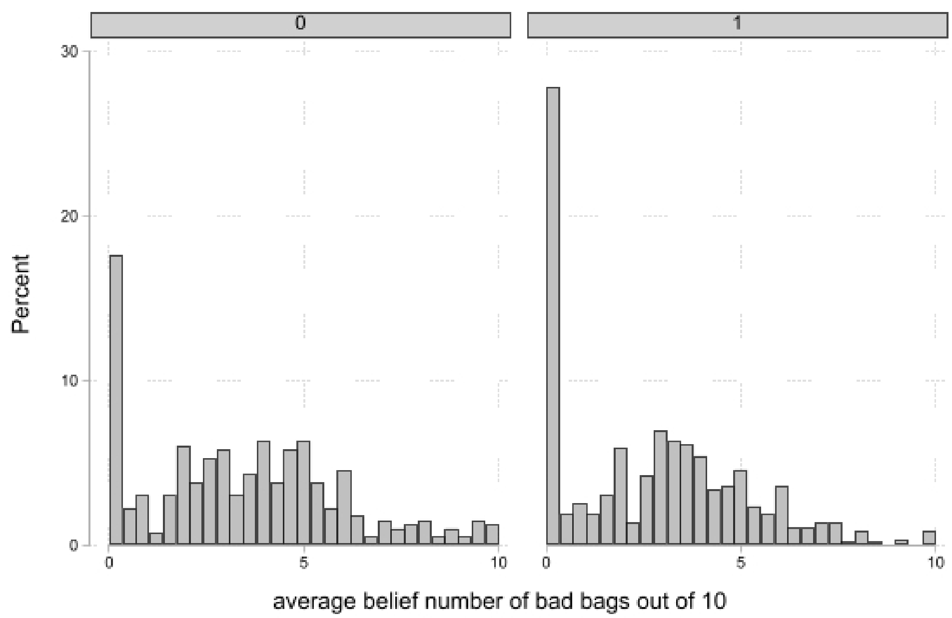


Figure A.4: Kernel density of urea price in KS per 50 kg bag as reported by agro-dealer at endline early 2020. All endline agro-dealers, comparing agro-dealers who have urea in stock with (82) those who do not have urea in stock (242)

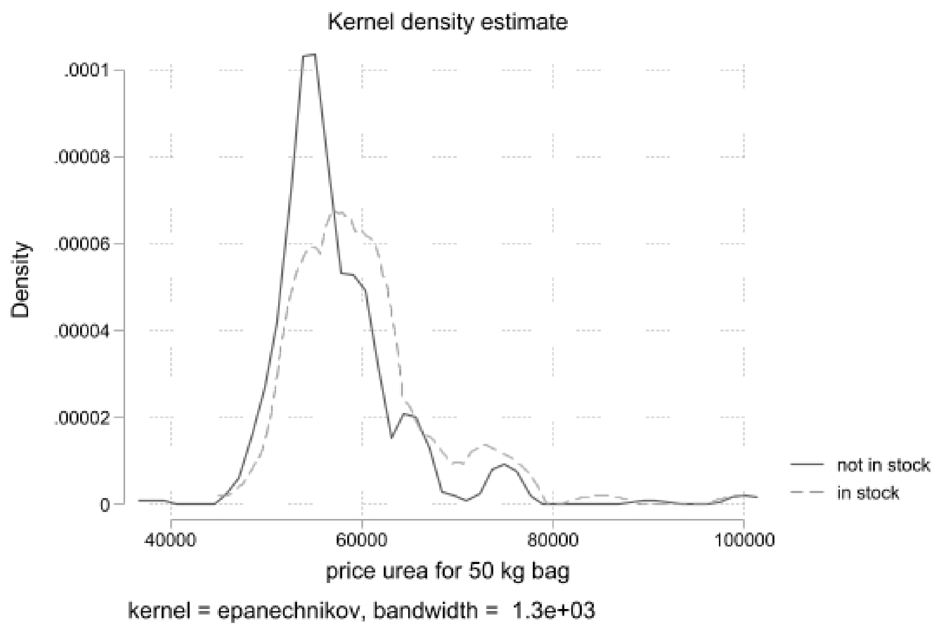


Figure A.5: Kernel density amount of urea sold kg/year by market treatment status at endline, agro-dealer data

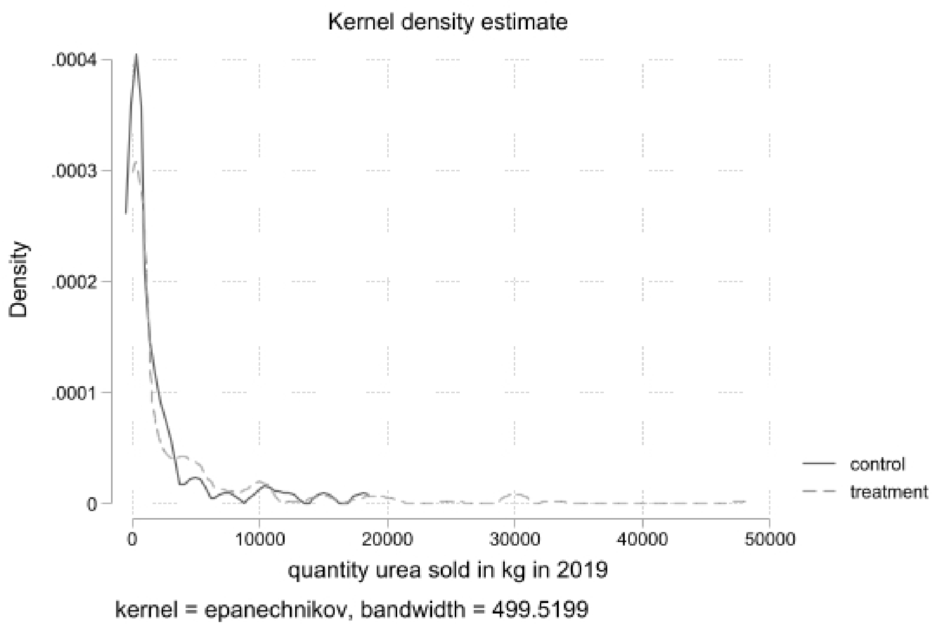


Table A.1: Test for differential attrition in the farmer sample

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)
Sex respondent (0 = male; 1 =female)	-0.0326	0.0185	-4.642
	(0.0387)	(0.0373)	(6.533)
Age respondent	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 balanced panel (analysis sample). Column (1) refers to ever having purchased fertiliser at baseline. Column (2) refers to having purchased fertiliser in the main long-rain growing season in 2018. 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: 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. There are 132 additional agro-dealers at endline, 22 of which should have been interviewed at baseline but were not, likely because no-one was available at the time (we found these agro-dealers were in existence for a more than one year at endline). There are 66 additional agro-dealers at baseline, 17 of which never sold prior to 2018 and should not have been interviewed at baseline following the updated definition. Recall that the definition of agro-dealers changed slightly between the two rounds. At baseline we defined agro-dealers as shops selling any agricultural inputs. At endline, we defined agro-dealers as shops having sold, currently selling fertiliser, or planning to sell fertiliser in the future.

Table A.4: Test for differential attrition in the agro-dealer sample

	Interviewed at endline
Market intervention	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.5: Test for differential addition in the agro-dealer sample

	Number of agro-dealers
Market intervention * after	0.120
	(1.215)
Market intervention	1.520**
	(0.763)
After	0.600
	(0.453)
Constant	2.220***
	(0.264)
Observations	200
R-squared	0.039

Note: This table uses a difference-in-difference specification to investigate the relationship between the number of agro-dealers in the market and the market intervention. Robust standard errors are reported in parentheses. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.01$

Table A.6: 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.7: Regression of fertiliser 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)
Sex respondent (0 = male; 1 =female)	-0.370*	-0.0761**
	(0.202)	(0.0352)
Age respondent	-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.8: 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

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. 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: 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*	0.00226**	0.0014191	0.005015***
	(0.000376)	(0.00110)	(0.0012784)	(0.0013676)
N of agro-dealers selling in both rounds	0.0763***	0.108**	0.0559	0.0657
	(0.0188)	(0.0507)	(0.0822)	(0.0550)
N of agro-dealers	-0.000162	-0.0162	-0.00769	0.00329
	(0.00511)	(0.0133)	(0.0218)	(0.0159)
Dummy for weekly visits to market		-0.145	0.346	-0.027
		(0.228)	(0.236)	(0.251)
Dummy for monthly visits to market		-0.211	0.201	-0.370
		(0.247)	(0.252)	(0.313)
Dummy for quarterly visits to market		-0.126	0.588*	-0.507
		(0.262)	(0.352)	(0.370)
Dummy for yearly visits to market		-0.730**	0.006	-1.450**
		(0.293)	(0.344)	(0.398)
Constant	0.157***	0.693***	0.154	0.849**
	(0.0186)	(0.238)	(0.308)	(0.329)
Observations	1,150	481	275	164
Number of farmers	407	368	214	120

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 50 kg of urea (Column (3)) and more than 50 kg of urea (Column (4)) in the last growing season. The base category of the visits is daily visits (with markets which were never visited excluded from the sample in Columns (2), (3) and (4)). Robust standard errors are reported in parentheses.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.01$.

Table A.10: Correlation between distances and beliefs in the control villages

Variable	(1) N bad quality (out of ten)	(2) Concern (1 = yes ; 0 = no)	(3) N bad quality (out of ten)	(4) Concern (1 = yes ; 0 = no)	(5) N bad quality (out of ten)	(6) Concern (1 = yes ; 0 = no)
Distance to nearest treatment village (km)	-0.00838	-0.000543			0.00616	0.00346
	(0.00913)	(0.00214)			(0.0195)	(0.00464)
Distance to nearest treatment market (km)			-0.0109	-0.00126	-0.0169	-0.00465
			(0.00977)	(0.00220)	(0.0208)	(0.00497)
Baseline dep var.	0.116**	0.143**	0.118**	0.143**	0.118**	0.145**
	(0.0517)	(0.0593)	(0.0517)	(0.0596)	(0.0517)	(0.0594)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	470	470	470	470	470	470
R-squared	0.033	0.036	0.034	0.048	0.034	0.049
Baseline mean	3.08	0.77	3.08	0.77	3.08	0.77

Note: This table presents the results of an OLS regression following an ANCOVA specification using the farmer analysis sample (balanced panel between base and phone endline survey) in the control villages. The dependent variables are the average number of bags with bad quality (out of ten) in Columns (1), (3) and (5) and whether or not the farmer has any concerns in Columns (2), (4) and (6). 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 A.11: Correlation between exposure to treatment markets and beliefs in the control villages

Variable	(1) N bad quality (out of ten)	(2) Concern (1 = yes ; 0 = no)	(3) N bad quality (out of ten)	(4) Concern (1 = yes ; 0 = no)	(5) N bad quality (out of ten)	(6) Concern (1 = yes ; 0 = no)
Distance to nearest treatment market (km)	-0.0109	-0.00126				
	(0.00977)	(0.00220)				
Visited treatment market at baseline (1=yes; 0=no)			-0.472	-0.0184		
			(0.294)	(0.0593)		
Associated market is treatment market (1=yes; 0=no)					-0.271	-0.118**
					(0.313)	(0.0513)
Baseline dep. var.	0.118**	0.143**	0.112**	0.143**	0.112**	.134**
	(0.0517)	(0.0596)	(0.0510)	(0.0588)	(0.0516)	(0.0594)
Observations	470	470	470	470	470	470
R-squared	0.034	0.048	0.037	0.047	0.032	0.055
Baseline mean	3.08	0.77	3.08	0.77	3.08	0.77

Note: This table presents the results of an OLS regression following an ANCOVA specification using the farmer analysis sample (balanced panel between base and phone endline survey) in the control villages. The dependent variables are the average number of bags with bad quality (out of ten) in Columns (1), (3) and (5) and whether or not the farmer has any concerns in Columns (2), (4) and (6). 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 A.12: The effect of the village intervention on (non-urea) fertiliser purchases

Variable	(1) DAP (kg)	(2) DAP (0/1)	(3) CAN (kg)	(4) CAN (0/1)	(5) Minjinju (kg)	(6) Minjinju (0/1)	(7) NPK (kg)	(8) NPK (0/1)	(9) SA (kg)	(10) 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.13: Summary statistics prices at endline

Variables	(1) Mean	(2) Median	(3) St. Dev.	(4) N	(5) Within govt. range
		Dealer-reported prices			
Price urea (TS/50 kg)	58,400	56,000	6,969	230	52%
Price DAP (TS/50 kg)	66,561	65,000	9,030	165	32%
Price CAN (TS/50 kg)	52,675	50,000	10,401	191	NA
Price NPK (TS/50 kg)	65,886	65,000	8,835	132	NA
		Farmer-reported prices			
Price urea (TS/kg)	1,299	1,200	354	373	
Price DAP (TS/kg)	1,448	1,450	367	93	
Price CAN (TS/kg)	1,255	1,200	257	37	
Price NPK (TS/kg)	1,483	1,500	260	10	

Note: This table presents descriptive statistics on fertiliser prices at endline. The top panel report agro-dealer data (from all endline dealers who had the relevant fertiliser in stock at the time of the interview) and is in KS/50 kg bag. The bottom panel reports farmer endline data (from all farmers who had purchased the relevant fertiliser during the 2019 long rain season). The fifth column indicates the percentage of reported prices which are within an 15% range of the price reported by the government extension agent (53,716 TS (as of Aug 17) for DAP, and 49,531 (as of Feb 20) for urea).

Table A.14: 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.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)	(5) Purchase at small market (1=yes; 0=no)	(6) Switch markets (1=yes; 0=no)
Village intervention	-0.0742	0.0723	-14.86**	0.123*	0.0606	-0.135
	(0.198)	(0.0746)	(6.858)	(0.0655)	(0.0681)	(0.0842)
Baseline dep. var.	0.233***	0.757**	0.479***	0.563***	0.501***	
	(0.0594)	(0.0727)	(0.156)	(0.0656)	(0.0659)	
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var. at baseline	1.39	0.61	25.45	0.45	0.45	
Constant	3.760***	0.0441	0.507	-0.0828	0.241	0.357*
	(0.304)	(0.188)	(17.49)	(0.269)	(0.252)	(0.180)
Observations	214	179	226	229	227	229
R-squared	0.177	0.614	0.376	0.397	0.293	0.069

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 endline). Columns (1) and (2) use the endline in person data. Columns (3) to (6) use the endline phone data and limit the sample to those farmers who purchased fertiliser in both seasons. 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). Robust standard errors are reported in parenthesis.***$p < 0.01$, ** $p < 0.05$, * $p < 0.01$.

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.[37] 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 (2016); Magruder (2018); Harou et al. (2022)).

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

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. However, combined with the other measures in place, it was an additional source of monitoring. Due to unbalanced attrition in these data we did not include these data in our formal analysis.

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 fertiliser 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 fertiliser tested contained 46% Nitrogen which is required. We have come with signs (see Picture A.6) 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.7). Further fertiliser 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.6: Appendix Picture 1: Poster

Note: Translation: The fertiliser 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 fertiliser met the international standards of quality. Urea fertiliser had a good quality.

Figure A.7: 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.