Underground Knowledge: Soil Testing, Farmer Learning, and Input Demand in Kenya *

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Abstract: In most emerging economies in sub-Saharan Africa, the use of agricultural inputs by smallholder farmers is not sufficient to replenish the soil nutrient stocks that are steadily depleted through crop cultivation. Usually farmers do not have comprehensive information about the fertility status of their soils as it relates to the availability of nutrients such as nitrogen, phosphorus, potassium, sulfur, and carbon. Consequently, this often leads farmers to choose sub-optimal combinations of inputs given their soil nutrient profile. Using a unique dataset that includes data from experimental auctions for agricultural inputs in Kenya, this study tests whether information from individual soil tests affects farmers' behavior and ability to optimize their input choices. Packages of both inorganic and organic inputs were auctioned with farmers divided into several soil fertility information treatments and a control group. Using a difference-in-differences methodology, the results from this study show that providing soil fertility information to farmers has significant effects on the demand of agricultural inputs, especially when differences between men and women are considered. Our study suggests that substantial crop yield improvements and poverty reduction can be attained through soil testing tied to targeted fertilizer recommendations.

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1 Introduction

Smallholder farming systems across sub-Saharan Africa (SSA) are suffering from stagnant crop productivity which, too often, is leading to food insecurity (Sanchez, 2002; Frelat et al., 2016). Rather than intensification of productivity (yield per area), growth in agricultural production in SSA has mainly been driven by expansion of croplands and soil nutrient mining, where insufficient inputs are applied to replenish those that are carried off by crop produce (Drechsel et al., 2001). The lack of input use by smallholder farmers leads to soil fertility degradation and a downward yield spiral (Ngetich et al., 2012; Tully et al., 2015; Zingore et al., 2015). Low crop yields and soil degradation often push farmers into a poverty trap, where poor yields lead to lower incomes, which further limit the amount of inputs that farmers can invest in their land (Barrett, 2007; Barrett and Bevis, 2015). Many initiatives are being undertaken to increase the rates and scale of nitrogen (N), phosphorus (P) and/or potassium (K) inputs for smallholder crop production in SSA, alongside adoption of improved crop varieties and agronomic practices. However, the cost of inorganic fertilizers required to return to levels of sufficient soil fertility are often not profitable over the short term, because of extreme soil fertility depletion (Antle, Stoorvogel, and Valdivia, 2006; Marenya and Barrett, 2009b). To achieve sustainable intensification, it is of key importance that inorganic fertilizers are used where they are most efficient and profitable.

Significant differences in soil properties and fertility status exist at various spatial scales creating large variability in crop responses to inputs between agro-ecosystems as defined by soil type and climate, up to fields in the same farm enterprise (Tittonell et al., 2008a,b; Kihara et al., 2016). It is shown, for example, that applications of nitrogen fertilizer are often unprofitable on soils with severely depleted organic matter (Marenya and Barrett, 2009a), or soils that are highly acidic (Burke, Jayne, and Black, 2017). While inputs of N, P, and K to soils are often essential for improving agricultural yields, organic inputs are also of great importance to prevent loss of soil functions and maximize agronomic efficiencies, as shown by the framework on Integrated Soil Fertility Management (ISFM) (Vanlauwe et al., 2010). Combining inorganic fertilizers with organics has been shown to offer major benefits for crop productivity (Palm, Myers, and Nandwa, 1997; Mateete, Nteranya, and Woomer, 2010), and suppression of pests and diseases (Bailey and Lazarovits, 2003). Currently, most smallholder farmers decide on the allocation of inputs across fields and crops based on perception of soil quality and previous yields, which is not sufficient and accurate enough for assessing soil nutrient deficiencies and optimizing use of inputs (Marenya, Barrett, and Gulick, 2008; Berazneva et al., 2016). The heterogeneity in soil fertility status and responses of crops to inputs, along with low fertilizer buying power of smallholder farmers, necessitate plot-specific information and recommendations to aid in management of inputs across land resources.

The need of decision support for input management by farmers in SSA has triggered multiple research and development projects into digital soil mapping and soil fertility information systems. Many tools and tests are available that provide reliable analysis of soil properties, like pH, soil carbon (C) content, and availability of N, P, and K that share significant relationships with crop productivity and input efficiencies. However, little understanding exists whether such soil fertility information, when presented to farmers, alters their behavior and leads to better optimization of their input choices. In this study, we test whether providing information to 884 Kenyan farmers in the form of soil tests and individualized input recommendations influences their demand for a number of agricultural inputs. Soil fertility information from the main maize growing field of each farmer was obtained through analysis with SoilDoc(R), a low-cost and highly mobile soil testing system.

In this paper, we develop a model that assumes that farmers are risk averse and develop a perception of their soil properties through exposure to information by a Bayesian process, which affects their willingness to pay (WTP) for a particular input. The model shows that the WTP for inputs may become more dispersed across individuals as farmers learn about optimal combinations of inputs for their particular soil levels and adjust their valuations accordingly. Dispersed changes in participant WTP indicate that farmers are learning and adjusting their valuation of inputs towards their own individual optimum according to their farm's soil nutrient levels. This change in farmer demands for inputs that correspond to their soil characteristics allows for more effective profit maximization strategies and consequently will likely improve household welfare.

To estimate WTP for this study, we use experimental auctions among small-scale farmers in western Kenya randomly chosen from village rosters. The experimental auctions for different organic and inorganic inputs follow a Becker-DeGroot-Marschak (BDM) methodology and were implemented in two rounds to measure changes in WTP after information transfers to the participants (Becker, DeGroot, and Marschak, 1964). To test the efficacy of different transfer strategies, the sample was randomly divided at the time of the survey into three treatment groups and a control: the first group received the soil test results and individualized recommendations on inputs; the second group received the soil test results and a comparison between their soil nutrient levels and those of their anonymous peers; and the third group received both treatments. The control group only received the results of their soil tests and recommendations after both rounds of the experimental auctions were complete. In total, 864 individuals within 546 households bid on 12 different input and quantity combinations in two separate auction rounds.

We first test to determine whether changes in WTP for the agricultural inputs are more dispersed among individuals as a result of the information treatments. Using a mixed model that includes random coefficient estimations, we find that compared to the control, the change in WTP is more dispersed, although the degree depends on the treatment and gender of the respondent. Overall, individuals who received soil test results and recommendations had the largest dispersion of changes in WTP. Using triple difference estimations (difference in bid round, difference between treatment and control, and difference in information type), we find that the effect of the first treatment are heterogeneous across input types and demographic groups. In general, we find the effects of positive recommendations for the use of inorganic inputs to be uniformly positive, while the effects of recommendations for the use of organic inputs are mixed and depend greatly on gender. We also find that when an individual's soil nutrient levels are compared with their peers as in the second treatment, the influence on their demand for inputs again varies greatly depending on the gender of the respondent. When both these treatments are combined in the third treatment, we find the effects to be attenuated, possibly due to differing directions of impacts for each information treatment.

Determining whether increased knowledge of farmers' own soil type and quality alters their behavior with regard to input demands can help answer whether widespread soil testing can contribute to moving farmers out of poverty by overcoming information constraints. At present, farmers are frequently unable to discern nutrient deficiencies through traditional means. Soil type and quality varies significantly across individual farms, even within small geographic areas in SSA (Tittonell et al., 2005, 2013); this limits their ability to learn about soil type and quality from their neighbors. High-resolution geo-referenced soil data that rely on interpolation also appear to be inadequate to estimate soil characteristics at the individual farm level (Berazneva et al., 2016). Therefore, it appears there is substantial value to the testing of individual farms and dissemination of the associated information.

This study adds to several strands of literature. A significant amount of previous research has analyzed the effects of information transfers on farmer behavior in the developing world. This study, however, appears to be the first that uses individual soil tests and personalized input recommendations as the focus of the information transfer. An important policy question is whether this method of information transfer is effective at helping farmers optimize their input usage. A major contribution of this research therefore is to demonstrate the positive welfare effects and favorable benefits relative to costs of using soil testing to improve the well-being and food security of small-scale farmers.

This research also makes a contribution to the experimental economics field. Several past studies looking at the effect of information transfers on individuals in the developing world have used data from experiments (Lybbert et al., 2013; Steur et al., 2013; De Groote et al., 2016), but as far as we know, this is the first study that uses a two-round BDM auction methodology to analyze data in the developing world.

The effect on behavior that arises from peer comparisons has also been explored in the behavioral economics literature (Goldstein, Cialdini, and Griskevicius, 2008; Ayres, Raseman, and Shih, 2009; Allcott, 2011). This study – which uses experimental auctions to discover how comparisons with other peers in a village influence the behavior of farmers with respect to agricultural inputs – is the first to examine this research question in a developing country context. Moreover, it is the first to examine differences in behavior by men and women that come from comparisons with their peers.

Finally, this research contributes to the literature on the role of gender in agriculture in the developing world. We find strong differences in organic input demand between men and women, which appears to be related to the lower access to organic resources among female farmers, in part due to lower levels of livestock ownership among female-headed households. This lower level of livestock ownership among women has also been found by Ndiritu, Kassie, and Shiferaw (2014) in Kenya. The results in this paper show the effects of lower livestock ownership on organic input demand and this suggests a possible reason for lower adoption rates of organic inputs among women.

The remainder of this paper is organized in the following manner: Section 2 discusses the literature on learning and information transfers, Section 3 discusses soil degradation and agriculture in the sample area, Section 4 presents the theoretical model, Section 5 describes the data and experimental design, and Section 6 discusses the empirical results from the mixed model and difference-in-differences estimations. We conclude with a discussion of this study's implications and policy recommendations in Section 7.

2 Learning and information transfers

A substantial literature exists that analyzes technology adoption and learning in the developing world (see Feder, Just, and Zilberman (1985) and Foster and Rosenzweig (2010) for extensive reviews). Feder and Slade (1984), for example, develop a model to explain the acquisition of information by farmers related to a new technology. Dividing information acquisition into both active (entailing a cost) and passive (costless) components, the authors find that larger farmers initially have advantages in information acquisition due to larger resource endowments, and that a critical level of information must be obtained by a farmer before technology adoption takes place. In their seminal paper, Foster and Rosenzweig (1995) develop a target input model where the optimal use of inputs, rather than profitability, is learned from both a farmer's own and his/her neighbors' experience. They find evidence that a farmer's own profitability using a novel input is influenced by the average experience level of his/her neighbors. A large number of studies has also emerged that focus on the role of learning from peers, including Bandiera and Rasul (2006), who analyze the likelihood of adopting a technology based on the share of a farmer's network links who have already adopted, and Conley and Udry (2010), who find that farmers tend to increase their fertilizer use when a neighboring peer has higher than expected profits using that particular fertilizer. More recently, Krishnan and Patnam (2014) find evidence that farmers rely more on their peers than extension agents when learning about a new technology, and Nourani (2016) finds differential impacts of weak and strong network ties on the learning process.

We also find in the literature that heterogeneity of growing conditions among farms limits the diffusion of information regarding technologies like agricultural inputs. Munshi (2004) finds that during the Green Revolution in India, the adoption of high-yielding varieties was more rapid for wheat than for rice. He concludes that this is due to the fact that wheat-growing regions have more homogeneous growing conditions than rice-growing regions, and therefore a farmer can gain more reliable information from his neighbor's experience growing wheat than growing rice. In the U.S. context, because GM soybean seeds are sensitive to individual farm characteristics, Ma and Shi (2015) find that the information impact from peers is less than that from self-experimentation. Meanwhile, Magnan et al. (2015) find a rather muted peer effect for an agricultural technology, laser land leveling, in India, in part due to the heterogeneity in production characteristics that lead to varying levels of yield improvements from using the technology. Perhaps most related to this study, Tjernström (2015) shows that heterogeneity in soil health within a peer network limits information exchange between peers regarding experiences using new hybrid seed varieties in Kenya. If farmers share or sell results of their soil tests among their peers, this may reduce uncertainty regarding soil heterogeneity. Fabregas et al. (2014), who are analyzing farmers' WTP for soil test information itself, find that farmers are not only willing to pay for soil tests on their own farms, but will also pay to learn of soil test results from neighboring farms as well.

Information transfers to individuals can in fact significantly alter demands for products and technology. The economics of advertising literature in particular has shown that information transfers can increase the ability of individuals to make optimal matches between the characteristics of the product and their preferences (Nelson, 1970, 1974; Grossman and Shapiro, 1984; Anand and Shachar, 2011). Johnson and Myatt (2006) demonstrate that this "real information" aspect of information transfers increases the dispersion in product valuations by individuals across a sample and rotates the demand curve, as individuals are able to more accurately determine the suitability of the product relative to their wants or needs. A number of empirical papers have demonstrated a strong effect of information transfers on behavior, often using experimental auctions to elicit incentive compatible WTP estimates (Lusk et al., 2004; Zheng and Kaiser, 2008; Messer et al., 2011; Rickard et al., 2011; Liaukonyte et al., 2012; Liaukonyte, Streletskaya, and Kaiser, 2015b, among many others). Rickard et al. (2011) show, for instance, that commodity-specific information transfers regarding fruits and vegetables lead to an increase in the dispersion of valuations, providing evidence of individuals matching their preferences to products as a result of the new information.

The behavior of individuals can also be affected through social norms or proscriptions (Festinger, 1954; Akerlof, 1980; Bernheim, 1994; Akerlof and Kranton, 2000). For example, studies show that farmers may not adopt a new technology or practice if it is antithetical to social traditions (Barrett, 2005; Moser and Barrett, 2006). Many microfinance interventions and savings groups take advantage of social norms to ensure payments or savings (e.g, Dupas and Robinson, 2013). Information provided to an individual regarding the characteristics or behavior of their peers can also significantly affect behavior. An example of this in a different context is that of Goldstein, Cialdini, and Griskevicius (2008), who show that informing hotel guests that the majority of their fellow guests reuse their towels decreases laundry costs more than using a normative message regarding environmental sustainability. Similarly, Ayres, Raseman, and Shih (2009) and Allcott (2011) find that providing information to utility consumers regarding the energy usage of their neighbors decreases energy consumption by a significant margin. It remains to be seen, however, if such effects also exist in the context of this study, that is, with respect to soil management in developing countries.

Whether information transfers to individual farmers affect soil management and agricultural practices has been analyzed extensively in the past. Impacts of traditional agricultural extension programs, which involve face-to-face interactions between farmers and trained agricultural agents, have been mixed (see Birkhaeuser, Evenson, and Feder (1991) and Anderson and Feder (2004) for reviews). As these reviews highlight, extension programs are often large and complex, expensive, and suffer from a lack of accountability, all of which decrease their efficacy. Moreover, there is often concern over data quality and the difficulty in proving causality in impact evaluations of these programs (Anderson and Feder, 2004). However, more recent studies such as Dercon et al. (2009) in Ethiopia, have found clear benefits of agricultural extension through the study's careful empirical design. In order to avoid the pitfalls of traditional agricultural extension, there has been increased interest in conducting information transfers to farmers through information and communication technologies (ICTs), made possible through the rapid expansion of mobile phone ownership (Aker, 2011). For example, Cole and Fernando (2012) find that a mobile phone agricultural advice service in India was highly popular and increased the adoption of effective agricultural inputs among participating farmers. In the same project area as this study, preliminary results by Casaburi et al. (2014) show that text messages sent to sugarcane farmers with information on the optimal timing of agricultural tasks increased yields by 11% compared to a control group.

There has also been an expansion of research that has looked specifically at women in agriculture. In SSA, plots managed by women tend to have lower productivity than men (Croppenstedt, Goldstein, and Rosas, 2013; Kilic, Palacios-López, and Goldstein, 2015; Oseni et al., 2015; Slavchevska, 2015). In part, this appears to be due to inefficient allocation of resources within the household, where plots managed by men receive relatively larger amounts of inputs (Udry et al., 1995; Udry, 1996). Women also tend to adopt agricultural technologies and practices at lower rates than men (Doss and Morris, 2001; Gilligan et al., 2014; Ndiritu, Kassie, and Shiferaw, 2014), and as shown by Karamba and Winters (2015) in Malawi, participation in input subsidy programs does not appear to close the gender gap. This gender gap likely due to several factors. Gilligan et al. (2014) suggest that the result is due to weaker household bargaining positions by women, although this would not necessarily account for the effect in female-headed households where males are absent. Doss and Morris (2001), Croppenstedt, Goldstein, and Rosas (2013), and Ndiritu, Kassie, and Shiferaw (2014) suggest that at least part of the explanation lies with the lower levels of resources available to female farmers. For example, if female-headed households tend to have lower levels of livestock, this would limit the adoption of manure or compost as organic fertilizers since markets for these inputs are not highly developed. Karamba and Winters (2015) thus emphasize the need for policies and programs to explicitly target women farmers in attempts to close the productivity gap.

As mentioned previously, farmers do not necessarily have accurate beliefs regarding their own soil nutrient levels, which may further limit their use of agricultural inputs. Perceptions of soil health are primarily based on yield, which not only is a lagged indicator, but does not necessarily inform the farmer precisely of which nutrients, if any, are deficient (Marenya, Barrett, and Gulick, 2008; Berazneva et al., 2016). Uncertainty therefore exists on the part of the farmer as to whether a particular input will be an optimal match for the soil characteristics of that particular farm plot, which according to the model developed in this study, will likely decrease input usage if the farmer is risk averse. Information transfers in the form of results from soil tests may thus be an effective remedy to increase agricultural input adoption and usage, and in turn generate higher yields and an escape from the poverty trap.

3 Soil degradation and agricultural input use in western Kenya

Western Kenya, where this research was carried out, has some of the highest population densities in SSA. The rural population mainly consists of smallholder farmers that rely on their own agricultural production for most of their food consumption. The agro-ecosystems in the area have highly weathered soils that contain clay minerals with poor exchange capacity for plant nutrients, making productivity of staple crops like maize, sorghum, and beans often far below attainable levels due to soil nutrient depletion, acidification and/or erosion (Sanchez, 2002; Tittonell et al., 2008b; Tully et al., 2015). The removal of nutrients from croplands through grain and biomass residues and the failure to sufficiently return adequate inputs to the soil is the major cause of soil fertility degradation in smallholder farming systems across the region. Compounding the problems faced by farmers, soils with low fertility are also more susceptible to pests, diseases, and weeds, especially Striga (witchweed), which has caused substantial yield losses in maize crops across East Africa (Mateete, Nteranya, and Woomer, 2010). As a result of low soil fertility, farmers often fall into "resource degradation poverty traps," where a downward cycle of falling crop yields and decreasing soil fertility lead to a continuing decline in farmer well-being (Barrett, 2007; Barrett and Bevis, 2015). For many farmers to escape this poverty trap, investment in agricultural inputs is necessary.

We find, however, in this research area, farmers are often investing in fertilizers, sometimes substantially. Inorganic fertilizers such as DAP (diammonium phosphate) are widely used across western Kenya as a source of nitrogen and phosphorus in crop cultivation.[1] Sheahan, Black, and Jayne (2013) demonstrate that in many areas of Kenya, including the area of this study, farmers are often using nitrogen fertilizers in excess of profitable levels. This comes after years of promotion and subsidization of nitrogen fertilizers, especially DAP, by the government of Kenya.

DAP and other inorganic nitrogen and phosphorus fertilizers are, however, not necessarily universally effective across farms or even on plots within the same farm. Without comprehensive information regarding the soil nutrient levels on a farm, there exists significant risk of 'non-responsiveness' – that is, that no satisfactory response in crop yields will be achieved with the input investments (Wopereis et al., 2006; Denning et al., 2009; Sanchez, 2010; Sileshi et al., 2010). A meta-analysis of maize fertilizer responses in SSA was carried out with data from 375 locations covering a large range of the climate types and soil types (Kihara et al., 2016). The study showed that maize grain yield responses to commonly recommended N, P and/or K inputs remained below 0.5 ton per hectare in 20 to 25% of smallholder fields. Another meta-analysis with data from 90 studies in SSA found that the use efficiency of inorganic N by maize crops did not exceed 5 kg of grain per kg of N in 12% of croplands (Vanlauwe et al., 2011). On-farm trials in part of this region by Roobroeck et al. (2017) found that universal application of inorganic fertilizer in line with government recommendations did not increase maize yields by more than one ton per hectare for 19 to 30% of farmers' fields, and didn't return a value/cost ratio for inorganic fertilizers greater than 2.0 in 59 to 63% of cases, thus leading to a frequent

[1] 84% of household heads in this sample report having used DAP at some point in the past, and 78% used DAP in the last long rain season.

loss on this investment for farmers. The same study revealed that the amount of 'good' clays in soils, its exchange capacity of nutrients, and rainfall irregularity had significant hierarchical relations with the fertilizer response of maize crops. The high risks of unprofitable input use in smallholder farming systems emphasize the need for delivering reliable and effective soil information to producers and other agricultural stakeholders.

While the vast majority of farms in this area are deficient in nitrogen and phosphorus, many farms also suffer from insufficient soil organic matter or have acidic soils. (For reference, table 1 shows the soil nutrient levels of farms in the sample, which were randomly chosen from small-scale farmers in the research area). Application of nitrogen fertilizers are often ineffective on soils that have low soil organic matter (Vanlauwe et al., 2002), making their use unprofitable (Marenya and Barrett, 2009b). In addition, the use of nitrogen fertilizers on acidic soils is ineffective, and can further acidify the soil (Bekunda, Bationo, and Ssali, 1997) again making their use unprofitable (Burke, Jayne, and Black, 2017). It is often difficult for farmers to have concrete knowledge whether crop yields are suffering due to a lack of nitrogen, phosphorus, organic matter, whether their soils are acidic, or combinations of these factors.

Insert Table 1

In sum, both organic and inorganic fertilizers play important roles in agricultural production. Conventional organic fertilizers, including animal manure and crop residues, have been used in traditional cropping systems for millennia to replenish soil nutrients. Organic fertilizers not only contain valuable soil nutrients such as nitrogen, but also can increase soil organic matter (carbon), reduce soil acidity, improve water retention, reduce the prevalence of pests and diseases, and increase beneficial microbiota in the soil (Ngetich et al., 2012). However, because of many factors including high transportation costs, most organic fertilizers are produced on-farm in the developing world (Place et al., 2003). This lack of developed markets leads farmers to face tradeoffs in allocating household resources for use as fertilizer. Animal manures and crop residues can both be burned for home energy use, especially for cooking, and crop residues are also commonly used as animal feed. Gathering, storing, and dispersing organic inputs are also labor intensive activities, as animals often graze in pastures and the manure must be found and transported, and mechanized tools such as manure spreaders are virtually non-existent. As a result, household shadow prices (opportunity costs) for these products are substantial relative to household incomes (Berazneva et al., 2017). Thus, although many households produce these inputs as byproducts, their high opportunity costs limit the intensity of their use and adoption as fertilizers.

Therefore, it could be beneficial for small-scale farmers in SSA to obtain access to relatively inexpensive, potent organic fertilizer substitutes. Included in the experimental auctions of this study are organic inputs have been introduced into Kenya to fulfill this need. One of these is biochar, a form of charcoal produced through the thermal decomposition of biomass at high temperatures in an oxygen-limited environment – a method known as pyrolysis (Bridgwater, 1994). Used as a soil amendment, biochar has the remarkable capacity to simultaneously decrease soil pH, increase availability and retention of soil nutrients, increase cation exchange capacity (CEC), increase soil moisture and organic matter, and decrease the prevalence of pathogens, among other benefits (DeLuca, McKenzie, and Gundale, 2009; Scholz et al., 2014). Biochar can be produced fairly simply in SSA on small farms using relatively inexpensive kilns with crop residues, animal manure, woodchips, etc., as feedstocks. However, due to the high opportunity costs of feedstocks, this process may not be economical for many farmers. There is growing interest in large-scale commercial production of biochar from organic solid waste, especially by producers of products such as sugar and tea that produce large levels of organic byproducts (Gwenzi et al., 2015). This commercial production could potentially generate large amounts of relatively inexpensive biochar for sale in SSA markets.

Compost is already known by many farmers in western Kenya, though this knowledge is not universal.[2] A type of compost known as vermicompost is another high potential organic fertilizer, which is produced through the decomposition of organic materials by earthworms (Jack and Thies, 2006). Rather than being broken down by microorganisms as with traditional compost, which is relatively labor intensive and takes up to nine months for decomposition, vermicompost requires little labor and is produced within two months (Ndegwa and Thompson, 2001). Moreover, vermicompost has proven to be superior to traditional compost and inorganic nitrogen fertilizers in many respects, including lower rates of nitrogen release, lower salinity stress, and significantly greater pathogen suppression, among other benefits (Chaoui, Zibilske, and Ohno, 2003; Jack and Thies, 2006). Like biochar, vermicompost can be produced by farmers on small-scale farms, but again, the shadow price of the feedstock may not make production economically viable. However, commercial production of vermicompost has already begun in

[2] 88.3% of household heads in this sample had heard of compost at the time of the survey, and 44.3% say that they or someone in their household has used compost in the past.

SSA (notably Kenya) at prices competitive with inorganic fertilizers.

Organic inputs such as animal manure, traditional compost, crop residues, biochar, and vermicompost can thus be extremely effective tools to aid in the recovery of degraded soil. However, they will not be equally effective on all types of soils and in many cases inorganic fertilizers should be used in addition to these inputs. Studies have demonstrated that organic and inorganic inputs should be used together to replenish depleted soils, as inorganic fertilizers have higher concentrations of nutrients such as nitrogen and phosphorus, while organic inputs help to replenish soil organic matter and control acidity (Palm, Myers, and Nandwa, 1997; Mateete, Nteranya, and Woomer, 2010). Thus, to enable farmers to assess whether they should spend valuable resources to acquire these inputs, knowledge of their soil nutrient levels is important. Therefore, we attempt here to determine whether information provided to smallholder farmers with nutrient deficient soils will alter their demands for agricultural inputs. We expect that these information transfers will enable farmers to form more appropriate matches between their soil and inputs, thus reducing farmers' uncertainty and optimizing their input use. Understanding the effects of these information transfers is valuable both to this particular study and potential policy interventions more broadly. This is explored further in the following model.

4 A simple model of farmer WTP

An objective of this model is to demonstrate the willingness to pay of an individual farmer for a particular input combination and the effect on farmer WTP of having received new information about his/her soils. We examine the case of a farmer is evaluating his/her expected profit using an input that differs from the input combination the farmer has traditionally used. It may be the case that for a particular farmer, the traditional input combination will be a null set. WTP in this context can be conceptualized as the difference in the utility to the farmer between the use of the novel input set (k, T) and the traditional input set (T). For producers, this utility is derived from differences in expected profits, and is known as a variation function (since compensating and equivalent variation are equivalent for producers (Just, Hueth, and Schmitz, 2004; Zapata and Carpio, 2014)). We model this variation function for farmer i in period t as:

$$E(d_{itk}) = E[\pi_{itk}^{k,T} - \pi_{it}^{T}] \tag{1}$$

where $E(\pi_{it}^{k,T})$ is the expected profits in period t, maximizing between a novel input k and traditional input set T, π_{it}^{T} is the expected profits in period t with solely the traditionally used inputs. In other words, the willingness to pay for the new input is the difference between the maximized profits of the farmer using both new and traditionally used inputs, and the profit maximization of the farmer if he had not used new inputs. Therefore, if farmer i has not yet adopted the new input, this value will be zero.

A simple representation of a farmer's profit function optimizing across new and traditionally used inputs is:

$$E(\pi_{it}^{k,T}) = E\left[P\left(A_{it}^{k}(x_{it}^{k})^{\frac{1}{2}}L_{it}^{k} + (x_{it}^{k})^{\frac{1}{2}}L_{it}^{k}\epsilon_{it}\right) - c_{t}^{k}x_{it}^{k}L_{it}^{k} + RL_{it}^{T} + \gamma L_{it}^{k} + \alpha_{i}\right] \tag{2}$$

where P is the per unit sale price for the crop, which is assumed to be fixed in the short run and known by all farmers in period t, and R is the net per acre returns using the traditional inputs. We let A_{it}^{k} be the product – and plot-specific agronomic efficiency that represents the farmer's soil suitability for that particular input k. Agronomic efficiency is defined as the increase in maize yield per unit of the input applied using the soil of farmer i (Vanlauwe et al., 2011). The agronomic efficiency for input k is not known by farmers with accuracy, but their estimate is distributed $N(\bar{A}_{it}^{k}, \zeta_{it}^{2})$. Then we define the accuracy of the estimate of the agronomic efficiency A by farmer i for product k as $\theta = \frac{1}{\zeta^{2}}$, or the inverse of the variance. Term x is the quantity of the new input used by farmer i in period t, and L^{k} is the number of acres on which it is applied (including land on which traditionally used inputs are also used), while L^{T} represents land on which only traditionally used inputs are used. Term c is the per unit price of the input x, which is assumed to be fixed in the short run and known by all farmers in period t. Stochastic variable ϵ represents weather or other variability: $\epsilon \sim N(0, \eta_{it}^{2})$. Term α_{i} is a measure of farmer expertise, ability, or other demographic characteristics such as education, which may affect profitability. We assume $L^{k} + L^{T} = L$, L is fixed in the short run, and for simplicity we assume that in estimating his/her expected profit, the farmer assumes s/he will continue to devote at least some land to the traditional set of inputs, thus $L^{T} > 0$. However, the farmer may not plan to devote any land to the new input: $L^{k} \geq 0$, thus $\gamma L^{k} = 0$.

If we assume that the farmer has CARA (constant absolute risk aversion)[3] risk preferences on the profit function in equation 2, we have:

$$E(\pi_{it}^{k,T}) = P\bar{A}_{it}^k(x_{it}^k)^{\frac{1}{2}}L_{it}^k - c_t^k x_{it}^k L_{it}^k + R(L_i - L_{it}^k) + \gamma L_{it}^k + \alpha_i - \frac{1}{2}\varrho P^2(L_{it}^k)^2 x_{it}^k\left(\frac{1}{\theta_{it}} + \eta_{it}^2\right) \tag{3}$$

where ϱ is the measure of absolute risk aversion. Expected profit is clearly increasing in the accuracy of the belief of the agronomic efficiency of θ, and in the mean of the perceived agronomic efficiency for input k, $\bar{A}^k$. We thus have the following FOCs:

$$\frac{\partial E(\pi^{k,T})}{\partial L^k} = P\bar{A}_{it}^k(x_{it}^k)^{\frac{1}{2}} - c_t^k x_{it}^k - R + \gamma - \varrho P^2 x_{it}^k L_{it}^k\left(\frac{1}{\theta_{it}} + \eta_{it}^2\right) = 0 \tag{4}$$

$$\frac{\partial E(\pi^{k,T})}{\partial x^k} = \frac{P_t\bar{A}_{it}^k L_{it}^k}{2(x_{it}^k)^{\frac{3}{2}}} - c_t^k L_{it}^k - \varrho P^2(L_{it}^k)^2\left(\frac{1}{\theta_{it}} + \eta_{it}^2\right) = 0 \tag{5}$$

Due to the complementary slackness condition, if $L^k = 0$, $\gamma \geq 0$, then

$$\begin{aligned} 0 \leq \gamma &= -P\bar{A}_{it}^k(x_{it}^k)^{\frac{1}{2}} + c_t^k x_{it}^k + R \\ R &\geq P_t\bar{A}_{it}^k(x_{it}^k)^{\frac{1}{2}} - c_t^k x_{it}^k \end{aligned} \tag{6}$$

From equation 6, we see that the farmer will not use the new input if the returns to the traditional input (R) are greater or equal to the net returns of the new input ($P_t\bar{A}_{it}^k(x_{it}^k)^{\frac{1}{2}} - c_t^k x_{it}^k$) for farmer i. Therefore, if the expected return to the new input k, $\bar{A}_{it}^k(x_{it}^k)^{\frac{1}{2}}$, increases, it would be more likely that the farmer would adopt the input. Receiving positive information related to the agronomic efficiency of input k would be one potential pathway for this to occur.

The variation equation for input k (producer's willingness to pay) from equation 1 will thus equal equation 3 minus the expected profits using the traditional input, $E[\pi^T] = RL_i$:

$$\begin{aligned} d_{it}^k = E[\pi_{it}^{k,T} - \pi^T] &= P\bar{A}_{it}^k(x_{it}^k)^{\frac{1}{2}}L_{it}^k - c_t^k x_{it}^k L_{it}^k + R(L_i - L_{it}^k) + \gamma L_{it}^k + \alpha_i - RL_i \\ &\quad - \frac{1}{2}\varrho P^2(L_{it}^k)^2 x_{it}^k\left(\frac{1}{\theta_{it}} + \eta_{it}^2\right) \\ = E[\pi_{it}^{k,T} - \pi^T] &= P_t\bar{A}_{it}^k(x_{it}^k)^{\frac{1}{2}}L_{it}^k - c_t^k x_{it}^k L_{it}^k + \alpha_i - RL_{it}^k + \gamma L_{it}^k - \frac{1}{2}\varrho P^2(L_{it}^k)^2 x_{it}^k\left(\frac{1}{\theta_{it}} + \eta_{it}^2\right) \end{aligned}$$

[3] We do not assume that it is generally the case that farmers have CARA risk preferences, but use it for tractability in the model.

Rearranging terms,

$$d_{it}^k = L_{it}^k \left[P\bar{A}_{it}^k (x_{it}^k)^{\frac{1}{2}} - c_t^k x_{it}^k - R + \gamma + \alpha_i - \frac{1}{2}\varrho P^2 L_{it}^k x_{it}^k \left(\frac{1}{\theta_{it}} + \eta_{it}^2 \right) \right] \tag{7}$$

which has the following FOCs,

$$\frac{\partial d_{it}^k}{\partial L^k} = P\bar{A}_{it}^k (x_{it}^k)^{\frac{1}{2}} - c_t^k x_{it}^k - R + \gamma - \frac{1}{2}\varrho P^2 L_{it}^k x_{it}^k \left(\frac{1}{\theta_{it}} + \eta_{it}^2 \right) = 0 \tag{8}$$

$$\frac{\partial d_{it}^k}{\partial \bar{A}^k} = P(x_{it}^k)^{\frac{1}{2}} L_{it}^k = 0 \tag{9}$$

$$\frac{\partial d_{it}^k}{\partial \theta} = \frac{-\varrho P^2 (L_{it}^k)^2 x_{it}^k}{2\theta_{it}^2} = 0 \tag{10}$$

We can see from equation 7 that if the amount of land on which the new input k is used is zero ($L^k = 0$), then the WTP for input k is 0. We can also see that WTP is decreasing with the cost of the input c, the net return of the traditional input R, and the variance, η^2, of the stochastic variable ε. WTP is increasing in the net profit of the new input, in the level of accuracy of farmer i's estimate of his/her agronomic efficiency of k on the soil of i, θ, and in the mean of the perceived agronomic efficiency for input k, $\bar{A}^k$.[4] The closer that the individual farmer believes that the input k matches his/her soil characteristics, the greater the perceived agronomic efficiency it will have, and the more s/he values input k.

4.1 Updating WTP

On learning new information about the farm-specific agronomic efficiency for input k, farmers will update their WTP. We assume that this information about the agronomic efficiency is not erroneous, and thus we can represent the updating of his/her WTP as Bayesian. Bayesian updating refers to individuals forming a posterior belief based on the prior belief and the observed evidence related to that belief (the likelihood of the belief). In this context, the farmer's belief on the agronomic efficiency of a particular input on his/her soil is proportional to the prior belief of the agronomic efficiency multiplied by the evidence related to that belief (in the information received).

Let us assume that the incoming information signal υ regarding the agronomic efficiency of k for the soil of i is distributed $N(\mu_{it}, \sigma_{it}^2)$. The inverse of the variance of the signal, $\frac{1}{\sigma_{it}^2}$, can be thought of as the trust the individual places in the accuracy of the information signal.

[4]One can also notice that from the specification used, equation 8 is the same as equation 4.

Thus, if we assume a standard Bayesian updating process (for example, as used by Foster and Rosenzweig (1995)), the accuracy of the farmer's belief in the agronomic efficiency of input k on his/her soil, θ, in period $t+1$ after receiving υ will be:

$$\zeta^2_{it+1} = \frac{1}{\frac{1}{\zeta^2_{it}} + \frac{1}{\sigma^2_{it}}}$$
$$\theta_{it+1} = \theta_{it} + \frac{1}{\sigma^2_{it}} \tag{11}$$

In other words, the accuracy of farmer i's information regarding his soil suitability in $t+1$ is equal to the accuracy in his/her belief in the previous period plus his/her trust in the accuracy of the new signal s/he has received regarding the agronomic efficiency of k on his/her soil. Thus, with each new information transfer, the farmer's beliefs in his/her soil characteristics will increase in accuracy. Again using a Bayesian process, the updated mean of the farmer's estimate of the agronomic efficiency of input k is:

$$\bar{A}^k_{it+1} = \frac{\zeta^2_{it}\mu_{it} + \sigma^2_{it}\bar{A}^k_{it}}{\zeta^2_{it} + \sigma^2_{it}} = \frac{\mu_{it} + \theta_{it}\sigma^2_{it}\bar{A}^k_{it}}{1 + \theta_{it}\sigma^2_{it}} \tag{12}$$

which states that the farmer's actual belief in the level of his/her soil characteristics and its compatibility with a particular input will increase if the information received indicates an agronomic efficiency greater than was believed previously, and will decrease if the information received indicates that the agronomic efficiency of a particular input is lower than the previous belief.

The model highlights that, holding all else constant, WTP will be increasing with any information received through an increase in the accuracy of beliefs. However, the effect on WTP through the change in the mean of the agronomic efficiency can be ambiguous: the model predicts that WTP will clearly increase if the new information indicates an agronomic efficiency of k greater than previously perceived $\bar{A}^k_{it+1} > \bar{A}^k_{it}$. However, if the information indicates the converse, then the direction in the change in WTP will depend on the magnitude of the two effects (stemming from the increase in accuracy and the decrease in the mean). If the effect of an increase in accuracy is greater than that of the decrease in the mean, then WTP will still increase. However, if the opposite is true, then WTP will decrease. While we would likely assume that WTP would decrease in this situation, if the effect of an increase in accuracy is very strong, equations 9 and 10 show this might cause an increase in WTP despite a decrease in the perceived compatibility between the farmer's soil and the input k. Therefore, it is ambiguous whether we will see an increase in the dispersion of WTP among participants for a particular input k, or if the impact of an increase in the accuracy of belief is particular powerful, a uniform increase in WTP. We would expect however that the effect from the updating of $\bar{A}^k$, the perceived agronomic efficiency of the input k on his/her soil, would be greater than the the effect that comes from θ, the increase in accuracy of his/her beliefs.

5 Data and experiment

We collected data for this research in three counties of western Kenya: Bungoma, Busia, and Kakamega. The partner organization, the International Institute of Tropical Agriculture (IITA), selected eighteen villages based on familiarity with the area. The villages covered a wide area of western Kenya (see map in Appendix A1 for positions of the sampled villages), mostly falling within the humid and sub-humid agro-ecological zones.[5] We obtained village rosters of household heads from village elders or regional chiefs, and randomly selected household heads using a random number generator. Staff from the project then visited each of the randomly chosen household heads, and after obtaining consent, took a sample of their soil.[6] To analyze the soil, we used the Soildoc wet chemistry system because it could be set up close to the fieldwork, is relatively inexpensive, and can be run with a local analyst who does not need high levels of special training (Earth Institute, 2017). The simplicity, reliability, and inexpensive cost of the Soildoc system creates opportunities to scale up the program and provide soil tests to many more farmers, potentially charging the actual per-test cost of about 2.50 USD (not including labor).[7]

After two or three months, the staff returned to the area from which they sampled the soils with the completed soil test information. In each household, we attempted to survey the household and wife individually, though in many instances, the spouse was not present and could not be interviewed.[8] The survey included questions household and individual demographic characteristics, household market activity, and agricultural production and practices over the past

[5]Because two villages were in direct proximity to one another, they were combined for the purposes of this study.

[6]The single sample was a mix of soils from several different parts of the household's primary maize plot.

[7]Additional information about Soildoc in Appendix A2.

[8]This was often due to migration, where the husband had gone to work long-term in a larger city, or where the household head was a widow/er.

two complete cropping seasons.[9] The final sample consists of 884 individuals in 548 households. Table 2 shows key summary statistics for the sampled individuals and households.

Insert Table 2

The table demonstrates that we captured a wide variety of individuals through the random sample selection. The average age and years of education of the respondent was 48.29 and 7.95 years respectively, with large ranges of each. Because the number of years of education does not necessarily capture the quality of education for an individual, we also tested their math ability at the time of the survey by asking each respondent to perform a simple multiplication problem, which 56% could answer correctly.[10] The final sample was majority women (58%), due in part to migration by many men to work in cities, and by the number of widows in the sample. While many individuals in the sample had more than one occupation, 88% identified farming as their primary occupation. Most individuals in the sample identified as Christian, with the plurality of respondents attending a Pentecostal/Charasmatic Christian church (42%). Also, because of where the sample was taken, most of the respondents are of the Luhya tribe (68%), though there were a significant number of Iteso represented (29%). The tribal affiliation was highly dependent on the county and village, with most Iteso from our sample in Busia county, the Bukusu (Luhya) subtribe in Bungoma county, and other Luhya subtribes from our sample in Kakamega county.

As previously mentioned, farms in the sample were generally very small (1.06 acres on average). This was in part due to design – we attempted to remove farms with significantly greater than average farm sizes from the village rosters.[11] Household sizes of the farms varied, with a mean of 5.29 people per household and a maximum of 40. We found household expenditures to vary greatly between households. If we only consider expenditures on food and drink, we find that average weekly expenditures were on average 1,228 KSh (about 12.00 USD), with a range from 0 to 21,000 KSh. Though most of the individuals sampled were women, a majority of the household heads in the sample are male (55%). While traditionally, men usually are household heads in Kenya, we found that women served as the household heads if they were a

[9]In western Kenya, the cropping seasons include the Long Rains season (March through August/September) and Short Rains season (October through January).

[10]The problem was 8*6+9. There was a divide between men and women who could solve the problem: 67% of men could solve it while only 48% of women were able to solve it.

[11]This was a requirement of one of our grants. Often, these large farms are owned by absentee landlords with farms managed by employees. The number of removed farms was very small however, and only amounted to one to five farms per village, in some cases, here.

widow, if the husband was away for work outside the village, or if the husband was sickly or a drunkard.[12] Most of the households use inputs on their agricultural plots, with 88% using at least one type of inorganic fertilizer over the past two completed cropping seasons at the time of the survey. The number who used organic inputs (e.g. animal manure) was less, 45% of households in the same time period. Only 7% of households in the sample did not use any inputs over both of these seasons. There were some connections with NGOs among households in the sample. Thirteen percent of households said that they had contact with an NGO in the past five years, with the majority of these saying the contact was with the One Acre Fund NGO. Many households have access to electricity: 13% in the sample are connected to the electrical grid, and 29% have solar panels. A significant number of households do not have access to clean drinking water (43% obtain their drinking water from a river), and most homes have mud walls (77%) and dirt floors (72%). However, 87% of the homes in the sample have a metal roof as opposed to a traditional thatched roof. Polygamy exists in the area; ten percent of households in the sample had a polygamous family structure. Livestock ownership is common in the region, with 63% of households owning at least one cow. On average, 33 households were sampled per village, and 52 individuals from each village were surveyed.

5.1 Experimental design

In this research, we use experimental auctions after Becker, DeGroot, and Marschak (1964) to estimate incentive-compatible WTP for agricultural inputs among individual respondents in our sampled households. Experimental auctions have been commonly used for decades in the industrialized world, but have only recently begun to be used in developing countries to elicit incentive-compatible estimates of WTP. Recent studies have used experimental auctions to investigate the demand for a variety of products, including insecticide-treated bednets in Uganda (Hoffmann, Barrett, and Just, 2009), biofortified rice in the Philippines and China (Corrigan et al., 2009; Steur et al., 2013, respectively), biofortified maize in Ghana (De Groote, Kimenju, and Morawetz, 2011), rice varieties in Senegal (Demont et al., 2012), laser land leveling in India (Lybbert et al., 2013), biofortified beans in Rwanda (Waldman, Kerr, and Isaacs, 2014), biofortified cassava in Nigeria (Oparinde et al., 2016), and aflatoxin free maize in Kenya (De

[12] Household heads were sometimes a challenge to define in households with polygamous family structures. In the sample, the women in these polygamous households often had their own farm, with the husband traveling between these farms. We defined the self-identified primary residence of the man to be male-headed, while the farms of the other wives are female-headed.

Groote et al., 2016). Many of these studies use a Becker-DeGroot-Marschak (BDM) methodology to obtain their WTP estimates, as they have been shown to be incentive-compatible and are convenient to implement at the individual level (Shogren, 2005). However, as discussed in De Groote, Kimenju, and Morawetz (2011), Morawetz, De Groóte, and Kimenju (2011), and **?**, precautions should be taken when transferring experimental auction methodologies used in the developed world to Africa, including the need for intensive training of auction experimenters and multiple test rounds for each participant.

BDM auctions, as we use in this research, are particularly suited to field experiments as participants make bids against a randomly generated price (Becker, DeGroot, and Marschak, 1964). This makes it possible to conduct the auctions with individual participants, which limits the bias that might otherwise arise from the respondent's observations of the behavior of other participants. While this methodology is somewhat more complex than more conventional auctions, with practice auctions to familiarize the participants with the methodology in Ghana, Morawetz, De Groóte, and Kimenju (2011) find that the increased complexity does not lead to bias in the WTP results when compared to a first-price auction. In our study, we used a two-stage BDM auction, where a baseline auction was conducted for the agricultural inputs prior to receiving the treatment, and a post-treatment auction was then conducted immediately afterward.

Prior to beginning the baseline auction for the inputs, the enumerator conducted practice auctions with the participants where the auction methodology was reviewed in detail (all auction scripts are in Appendix A3). The enumerator explained to the participant that s/he would receive a cash endowment and make bids for several items, and afterward, one item would be chosen at random and a random price would be chosen for that item. If the respondent bid at least the amount of the random price, they would pay that random price and receive the item. Otherwise, they would keep the cash endowment. The enumerator gave each participant 70 KSh (about 0.69 USD) and the participant bid on different varieties of cookies and 50 KSh cash notes.[13] After this first practice auction, the enumerator gave each participant another 70 KSh and repeated the practice auction. In a few cases, if it was clear that the respondent still did not understand the methodology, a third practice auction was conducted.

For the actual experimental auction, each participant was given a cash endowment of 700

[13]The motivation for auctioning cash notes is to emphasize that the participant should be bidding what s/he perceives as the true value of the good. Thus, for a 50 KSh cash note, the participant should bid 50 KSh. If they did not, then the enumerator would explain to the participant why this is the optimal strategy.

KSh (about 6.90 USD at the time of the research). In choosing the amount of the cash endowment, we needed to ensure that the endowment was sufficient enough that the participant could bid his/her true WTP. If it was too little, the bids might be biased downward. On the other hand, some research has shown that a larger cash endowment can lead to overstated WTP estimates (Loureiro, Umberger, and Hine, 2003). Adding to this concern is that the majority of the farmers in this area are poor, and average agricultural wages are about 300 KSh per day. Thus, 700 KSh is about twice the value of the more expensive quantities of goods that we were auctioning, and is therefore a standard cash endowment in line with the literature (Morawetz, De Groóte, and Kimenju, 2011; De Groote et al., 2016). We found that in our experiment 95% of bids were below 500,[14] and the mean bid across all inputs was about 200, thus we conclude that this was an effective choice for the cash endowment.

In this study, the auction was first conducted with the household head, and the spouse (if present) was asked to leave. After receiving the cash endowment, the enumerator read a brief statement that described some of the inputs that might be new to the participant (script used by enumerators included in Appendix A3). The participant then made bids on the agricultural inputs in varying quantities and presented them in a random order.[15] After all of these bids were collected, the enumerator's tablet computer randomly assigned the participant into one of four treatment groups:

Treatment 1 (Input Recommendation [IR]): Enumerators presented the participants with their soil test results, explaining them thoroughly and providing fertilizer recommendations tailored for their farms, developed for this project by the International Institute of Tropical Agriculture.

Treatment 2 (Village Comparison [VC]): Enumerators showed the participant a chart that compared their soil test results with other anonymized test results in their village and a village average. The enumerator pointed out their placement on the village distribution but provided no specific fertilizer recommendations.

Treatment 3 (Combined treatment [IR&VC]): Participants in this treatment received

[14] 98% of bids were below 700. If a respondent bid greater than 700, the enumerator was instructed to remind the participant that they would be responsible for payment above 700 if necessary and asked them to confirm their bid.

[15] The items offered for bid were DAP, biochar, a biochar DAP mix, vermicompost, a biochar vermicompost mix, and cow manure. Each were offered at 1kg and 5kg, except for the cow manure, which was offered at 5kg and 25kg quantities.

both Treatments 1 and 2 together.

Control: Participants received no information transfer between auction rounds.

Participants assigned to Treatments 1 and 3 received a copy of their soil test results that included a binary indicator of whether using an associated input type would increase their soil health (sample shown in Appendix A4). The enumerators, who had been extensively trained in making input recommendations based on the soil test results, then gave a detailed explanation of the meaning of the soil tests, and how the farmers could optimize their input usage based on this information. For example, a farmer with low nitrogen or phosphorus was advised to use DAP, CAN, or NPK fertilizer, unless their soil was acidic, then it was usually advised to avoid DAP because of its potential to further acidify the soil. With low carbon levels, compost, animal manure, biochar, and crop residues were usually recommended. The enumerator also explained the benefits of the complementary use of inorganic and organic resources in improving soil health. After these recommendations, the enumerator answered any questions the respondent had.

If the participant was assigned to Treatments 2 or 3, they were presented with a chart that showed their soil nutrient levels compared to others in the village (Appendix A4). The enumerator showed the participant his/her placement on the chart, and also identified the average in the village. Because most soils in the sample were of poor quality, the enumerator explained to the participant that this was a relative position, and explained where the threshold was for adequate levels of the nutrient in the soil. However, for those in Treatment 2, no input recommendations were made to the participant. For consistency, those participants in Treatment 3 always received the soil test results and recommendations before seeing the village charts.

Immediately after the baseline auction (and before receiving any treatment) each participant played a five minute memory game on the enumerator's tablet computer. This was done primarily so that the control group would have an activity between the two rounds, and for consistency this was done for all participants. The second auction round proceeded exactly as the first. Afterward the tablet computer randomly chose one auction round (the baseline or the second round), one product, and a random price. If the participant had bid at least the amount of that random price for that item in that round, they paid the random price and received the input, otherwise, they kept the full cash endowment.

5.2 Sample from experiment

By having the tablet computer assign the treatments between the auction rounds, we prevented any possibility of bias arising from prior knowledge of the participant's treatment group by the enumerator. The downside to this method was that this created unevenly distributed participant numbers in treatment groups, as Table 3 below illustrates:

Insert Table 3

We find that the random allocation by the tablet computer resulted in a difference of 28 individuals between the treatment with the most individuals (Treatment 1) and those with the least (Treatment 3). We see in particular that there are somewhat fewer men in treatment 3 than any of the other treatments and the control (77 compared to 96 to 101).

Because individuals were randomly assigned into the various treatment groups and control, we would assume that there would be no significant differences in the characteristics of individuals between the various groups, nor in the likelihood of a particular enumerator implementing that treatment. In Appendix A5, we include balance tables (Tables A5_1 through A5_4) that show average differences between those in a particular treatment/control group and those who are not in that group. Overall, these tables demonstrate that the randomization was effective, as most variables are balanced. One notable exception is farmland area, which is the only variable that is unbalanced in more than one treatment group (Treatment 1 and control). The magnitude of the difference however is not particularly large (0.92 and 1.17 for Treatment 1 and non-Treatment 1 respectively, and 1.29 and 1.04 acres for Control and non-Control respectively); we include this variable in all regressions to help prevent bias from this imbalance affecting the estimation results.

Overall, we have 884 individuals making bids in two auction rounds for two quantities of six inputs, providing a total bid sample of 21,216. To avoid making any inferences based on extreme values, we decided to trim the sample in two ways. First, we took the difference between the second bid and first bid for a particular input-quantity for an individual, and dropped both bids if the difference was in the top or bottom 1% of the sample. These were individuals who changed their bids by extreme amounts between auction rounds. This amounted to 358 total bids or 1.7% of the sample. We next dropped any remaining bids that were at least double the cash endowment (1,400 KSh), as these may not have been realistic bids by participants. This eliminated another 42 bids. The final sample size of all bids for both auction rounds used in the analysis is 20,816.[16]

Table A5_5 in the Appendix shows the average bids and standard deviations for each input by treatment and by auction round.[17] Five kilograms of DAP was on average the product with the highest average bid, followed by 25 kgs of cow manure, while 1 kg quantities of many of the organic inputs had the lowest average bids. In the baseline auction, average bids between treatment groups tended to be relatively close to one another, as we would expect given their random assignment. There does not appear to be a common pattern among the changes in means between auction rounds, as average bids for some inputs increased and other decreased between rounds across the treatments. Because each individual received different information, it is difficult to judge by these averages alone whether the information increased bid dispersion and led to changes in farmer behavior. To answer these questions, we use random coefficient estimations and difference-in-differences estimation as detailed in the following section.

6 Results

We use the data that we have collected in two primary ways to estimate results from the treatments. First, guided by our model and using random coefficient estimations, we seek to learn whether the information treatments have caused an increase in the dispersion of bids. This would suggest that farmers are updating their valuations to better match what they now perceive as the most effective match between their own soil health and agricultural inputs. Secondly, using difference-in-difference estimation, we take a closer look at the precise input recommendations (for Treatments 1 and 3) and placement on the village charts (for Treatments 2 and 3) and analyze in what direction and degree these treatments affect the farmer valuations of different types of inputs. We find that the treatments do have an impact, but the impacts are heterogeneous across gender and input type. (In a forthcoming version of this paper, we will also look at a cost-benefit analysis of the soil tests and welfare analysis, and will explore further mechanisms behind some of our findings presented here.)

[16] By trimming the sample, there were no individuals who were completely eliminated, and the number of individuals remains at 884.

[17] The uneven sample sizes in table A5_5 are due to the trimming of the sample.

6.1 Effect of the treatments on the dispersion of bids

As we saw in the model, the WTP for an input will likely become more disperse as individual i updates his/her belief about the agronomic efficiency ($\bar{A}^k_{ij}$) of input k on his/her soil. Those in Treatment groups 1 and 3 received soil test results and input recommendations that explained to them how efficient each would be at increasing the soil health on their farm. Treatment 2 (and 3), on the other hand, saw comparisons of their soil health with their peers, which we expect would also cause changes in their demand for various inputs. In Figure 1 and Table 4, we show the distributions of the changes in bids and the associated summary statistics, respectively.

Insert Figure 1

Each box plot represents a distribution of the changes in bids for all inputs for each treatment by gender.[18] As can be seen in the figure and table, the median across all the distributions is zero, while the means across the bids are near zero. If we compare the distributions of the treatment groups to those of the control for each gender, it appears that the treatment groups are significantly more dispersed. This would indicate that those in the the treatments groups altered their demand more than those in the control groups, suggesting that farmers are optimizing their input valuations based on the information received in the treatments. This is especially true for men, although there are many non-zero observations for the control group. The control group for women does have a visible distribution however, which means that significant numbers of respondents, were changing their bids based on receiving no new information. The reasons for this are not clear, but when the researchers asked respondents why they responded in this fashion, they would often say that they just "changed their mind." This may point to the lack of sufficient information for the respondent to make a serious bid, such as lack of experience using any kind of agricultural input or in purchasing inputs from the market. We also see in Table 4 that the standard deviations of the bids in the various treatments appear similar, and bids in the control group appears to have a significantly lower standard deviation, at least for men, again suggesting that an increase in dispersion occurred as a result of the information treatments.

Insert Table 4

[18]The interior line of the box plot is the median, the box itself is the observations within the first to third quartile (interquartile range, 75% of the data). The bottom tail is the first quartile minus 1.5 times the interquartile range, and the top tail is the third quartile times the interquartile range. The dots are observations outside of these ranges.

To determine whether there is statistical evidence of an increase in dispersion among the treatment groups compared to the control, we first use Levene's test statistic (Levene, 1960) to look for statistical differences between the group standard deviations.[19] We first test whether there is a statistical difference among all the groups. We find that whether we test in the overall sample, or that for men or for women, we can reject the null hypothesis that the standard deviations are the same across all the groups (at the 1% level). In Table A6_1 in the Appendix, we also include the results from these tests between each treatment group for both men and women. These results indicate that for men, women, and overall, the variance of each treatment group is statistically different from the variance of the control group. This provides evidence that the various treatments that provided information to the respondents caused an increase in the dispersion of bids when compared to the control group. This points to the treatments causing changes in behavior among the participants by increasing the extent to which the participants in the treatment groups changed their bids after receiving new information compared to those in the control group. There is mixed evidence as to whether there are significant differences in the level of bid dispersion between treatment groups however. We do not see a difference between Treatments 1 and 3, though overall and for men, there are statistically significant differences between Treatment 2 and Treatments 1 and 3. Based on these statistical results, it appears that Treatments 1 and 3 may have had a stronger influence on farmer behavior than Treatment 2, suggesting that Treatment 2 is less effective at influencing farmer behavior.

These test statistics, however, are insufficient to make broad conclusions, as they do not take into account individual, household, or village level characteristics that may influence that magnitudes of the bid change and thus the overall dispersions between treatments. A more accurate picture of the effect of the treatments on bid dispersions can come from using a mixed model that includes both fixed and random coefficient estimates to analyze the differences in the dispersion among the treatment groups and the control.

Because we treat the individuals as a random sample from the full population of farmers in western Kenya, we model the between-individual variability of their change in bids as a result of the treatments as a random effect: the impact of the treatment on the bids between individuals is considered random within their treatment group. As we have seen from the distribution statistics in Table 4, the fixed effect (mean) in each treatment is near zero. Thus, the

[19] We use this test statistic rather than other possible options because this test does not have any assumptions on the underlying distribution from which the data was chosen.

primary interest here is to measure the effect of the treatment through the variability between individuals. Treatments that cause behavioral changes will have created large differences in the bids between auction rounds among individuals, as each randomly chosen individual receives personalized information (aside from those in the control group). In our random coefficient estimations, an individual treatment impact is estimated for each individual. The variance of these individual treatment impacts is a way of estimating the dispersion in the change in bids due to each treatment (Liaukonyte, Streletskaya, and Kaiser, 2015a).

Thus, we estimate the following mixed model:

$$\Delta d_{ijk} = \delta first_{ijk} + \sum_{n} \phi_{in}\beta_n + \sum_{j} u_{ij}\tau_j + \sum_{k} \omega_k + \xi + \varepsilon_{ijk} \tag{13}$$

where the subscript j represents the experiment treatments (IR, VC, IR & VC, and control), Δd is the difference between the two auction rounds for input k in treatment j for individual i, ϕ are observable demographic, household, and farm characteristics for individual i (including observable aspects of α (farmer knowledge), and P (value of maize)), ω_k is a fixed effect for each input type, ξ are fixed effects for village, survey month, and enumerator, and ε are i.i.d. errors. Variable $first$ controls for the bid by each individual for each input in the first auction round, and u measures the individual-level impact of the treatment on the difference in auction bids between the two rounds.

To test for differences in the level of dispersion between treatment groups, we divide u into fixed and random coefficient estimates:

$$u_{ij} = \bar{u}_j + \lambda_j\psi_{ij} \tag{14}$$

The fixed component, $\bar{u}$ estimates the effect of the treatment j on the mean of the distribution of the change in bids, while λ measures the effect of the treatment on the level of dispersion of the distribution. The unobserved random variability between individuals, ψ_{ij}, captures the heterogeneous impacts on the change in bids within each treatment group (Berry, 1994). Variable ψ_{ij} is distributed $N(0, D)$, where we assume all covariances in D are zero.[20] By combining equations 13 and 14, we can estimate a model to analyze the effect of the treatments on the dispersion of the change in bids between individuals by treatment group.

[20] This is primarily due to computational limitations, but since the auctions were held independently from one another, we would assume that independent variances in this context are likely to exist.

Insert Table 5

Table 5 shows the results of the mixed model estimation on the difference in bids between rounds.[21] The upper section of the table shows the effect of the treatment on the mean of the distributions. Overall and for men, the mean of the change in bids between auction rounds increased, while for women it decreased. However, because each household has different soil characteristics on their farm, the information received might have influenced the participant's bids in either a positive or a negative direction, and so the mean does not necessarily tell us about the efficacy of the treatment compared to the control. On the other hand, the standard deviation segment of the table is more informative as it shows the variation in the impact of the treatment among individuals on the magnitude of their change in bids, hence providing us with an estimate of the effect on the dispersion of bids by that treatment. A higher standard deviation means that the treatment caused greater variability between individuals and more dispersion in the change in bids, while a lower standard deviation means that the treatment caused relatively little change in bids between individuals. We see that for the overall sample and for men, the standard deviation estimates for the between-individual effect of the treatments is significantly greater than for the control. This is especially true among men in the sample, where the standard deviation estimate for the between-individual treatment effects range from 25.02 to 29.17, and for the control is 9.05. This shows a very tight distribution of bid changes for men in the control group, suggesting that the control treatment did not cause men in the sample to behave very differently from one another. We find a surprisingly different effect among women in the control group compared to the treatments. The standard deviation estimate for the between-individual effect of the control group is higher than two of the other treatments (VC and IR & VC), indicating that women in the control group behaved very differently from one another while receiving no new information.

The striking difference between men and women in the sample in the difference in the level of bid dispersion between treatments and control is likely due to differences in their access to and experience with agricultural inputs. As we will discuss in additional detail in forthcoming versions of this paper, using crop-plot level data over two growing seasons, we find that women are less likely than men to use agricultural inputs on crops that they manage, especially organic inputs. With relatively less experience using inputs, women are less able to make informed bids, and are thus less anchored to their original bids. This leads to these participants simply

[21] To allow comparisons among the results of all treatments, we suppress the regression intercepts.

changing their mind between rounds, even when presented with no new information.

The large changes in bids in the control group among women may lead us to conclude that the treatments had less of an effect on this population. After all, among women, these results suggest that the control group appears to have influenced behavior as much as any of the treatment groups. This may be the case, but this analysis using the mixed model does not take into account the type of information received within each treatment and the direction in which the bid changed. For example, we need to compare a woman in treatment 1 who received information recommending using organic inputs to a woman who would have been given the same recommendation, but did not receive any information as she was in the control group. We can do this using difference-in-differences estimations that are discussed in the following section.

6.2 Difference-in-differences estimation

In this research, soil was collected from 548 farms in western Kenya and the results were later shared with the participants in different information treatments. The participating individuals on each farm were randomly placed into one of four groups: they either received input recommendations (IR), their soils were compared with their village peers (VC), received both these treatments (IR&VC), or were in a control group (see section 5.1 above for details about each treatment). Each of the household farms in this survey has a unique soil profile, which means that the particular information that each household receives from each treatment is also unique. For example, a participant within the IR treatment may receive a recommendation to use organic inputs if their soil is depleted in carbon, while their neighbor may receive a different recommendation. Therefore, it is not only the treatment that affects the behavior of each individual, but the information received with each treatment. To analyze the effects of the information, we therefore use a difference-in-differences estimation with three differences: the auction round (first and second), treatment status (particular treatment and control), and information type (treatment specific – in Treatment 1 for example, this is the difference between those who received a positive recommendation to use a particular type of input, and those who were recommended not to use that input.)

A key assumption of the difference-in-differences estimation is the parallel path or parallel trend assumption, or that the two groups being compared would have the same trend in the absence of any treatment (Angrist and Pischke, 2008). Because we are using triple-differences, we have two sets of parallel paths that should hold: the difference between the treatment and control, and the difference between the type of information received. The parallel paths assumption in the former should hold based on the random assignment: both the treatment and control were randomly assigned at the time of the auction and the characteristics among these groups are well balanced on the whole (see tables A5_1 through A5_4). In the latter case, the parallel path assumption for the difference in the information treatment is less clear-cut. If parallel paths existed, this would mean, for example, that individuals in treatment 1 who receive information advising them to use more organic inputs would, in the absence of treatment, behave in the same way as those who received advice that they do not need to use organic inputs. Because farmers have limited knowledge of the nutrient levels of their soils, especially with respect to specific nutrients, the parallel path assumption seems plausible. Using the control group as a guide, we show estimation results in Appendix A7 (Tables A7_1 and A7_2) that support this assumption. We conclude that there is sufficient evidence to support the existence of parallel paths in this sample.

We therefore perform triple-difference estimations for each treatment, comparing the impact of each treatment compared to the control:

$$
\begin{aligned}
d_{ikt} = \alpha &+ \delta_1 round_t + \delta_2 treatment_i + \delta_3 info_i + \delta_4 (round \times treatment)_{it} + \delta_5 (round \times info)_{it} \\
&+ \delta_6 (treatment \times info)_i + \delta_7 (round \times treatment \times info)_{it} + \sum_n \beta_n \phi_{in} + \sum_k \omega_k + \xi + \varepsilon_{ikt}
\end{aligned}
\tag{15}
$$

where $round$, $treatment$, and $info$ are binary variables. The variable $round$ indicates the auction round t, $treatment$ indicates whether the individual is in the treatment or the control, and $info$ is the information type that the individual receives (or would have received if in the control group). For example, in treatment 1, $info$ would be equal to 1 if an individual either received a recommendation that s/he should use input k on his/her farm, or would have received this recommendation given his/her soil test results but was in the control group. Interactions between these variables are included, and the coefficient of interest, δ_7, measures the impact of the information on those in the treatment group after the second auction. Exogenous characteristics of the individual, household, and farm are given by ϕ_n, ω controls for the input type k, ξ are fixed effects for enumerator, survey month, and village, and ε are i.i.d errors. Additionally, given the strong differences in results between men and women in the mixed model, the difference between men and women is also added to our estimations.[22] In many of these "quad-difference" regressions, we find surprising results that are detailed in the following subsections.

6.2.1 Difference-in-differences results: Treatment 1

We first look at the results of the triple and quad differences for treatment 1 (input recommendations). In this treatment, the individual receives the results of his/her soil test and the enumerator also makes targeted recommendations based on these results (more information about the treatment is in Section 5.1 and an example of a soil test result is in Appendix A4). If the participant has a farm with low soil nitrogen levels, the enumerator would recommend using DAP (unless the soil was also acidic, as DAP can have a acidifying affect), CAN (calcium ammonium nitrate fertilizer), or NPK (nitrogen phosphorus potassium fertilizer). If nitrogen levels were high, the enumerator informed the farmer that the use of nitrogen inputs was not a priority. On the other hand, if active carbon was low, the enumerator would recommend the use of animal manure, crop residues, compost, etc. For each individual, we create a variable (Use N), which is 1 if a nitrogen input (DAP) is recommended (78.12% of individuals), and 0 otherwise. Likewise, we create a variable (Use O) for organic inputs (e.g. animal manure), which is 1 if an organic input is recommended (66.21% of individuals), and 0 otherwise. Those in the control group also have observations for this variable, indicating the potential treatment that was never received during the experiment.

Table 6 shows the results of these estimations. Looking first at the results of the treatment on bids for DAP, we see that in the triple difference estimation (column I), those in the treatment who received a positive recommendation for inorganic nitrogen fertilizers (Use N) on average bid 60.71 KSh more than those in the control group who would not have received the recommendation (if they had been randomly chosen to be in the treatment). As way of comparison, the average quantity was about 2.5kgs, which has a market price at the time of the survey of about 200 KSh. Therefore the recommendations appear to have had an economically meaningful effect.

Insert Table 6

In our estimations, we use clustered standard errors to control for possible within-village

[22]We show in Appendix A7 that the parallel path assumption still holds with this additional difference added.

dependence between individuals, but the small number of village clusters (17) may lead to underestimates of the standard errors. Therefore, we also estimate adjusted p-values using the wild bootstrap method after Cameron, Gelbach, and Miller (2008), which corrects for the small number of village clusters. For the triple difference estimations in column I, both of the p-values from these methods are near zero, and the results appear to be highly statistically significant. If we move to column II, which has results for the quad differences, we see that including the difference between men and women lowered the average impact for men (46.30 KSh) and for women the results are positive but not statistically significant (25.48 KSh). This is likely in part due to the high variability in bids in the control group for women, which led to higher standard errors in the estimation. However, this estimation does tell us that the impact of the information recommending DAP fertilizer use for men and women is likely in the same direction for both genders, and that these recommendations were effective at leading farmers to optimize their valuation of DAP fertilizers with respect to their farms' soil characteristics.

Columns III and IV on Table 6 show estimation results for bids by participants on all organic inputs.[23] Looking at the triple-difference estimates, we find the those in the treatment group who received a recommendation to use organic inputs increased their bids by a modest 15.93 KSh compared to those in the control group who would not have received the same recommendation. When we use a gender difference in a quad-differences estimation, however, we find that for men, the information treatment appears to have had no effect. For women, however, we see an increase in the average bid by 32.47 KSh, significant at the 5% level (10% level with the wild bootstrap). The cause of these estimation results likely goes back to the different levels of access that men and women have to organic inputs. When we break down the data to the crop-plot-season level, women use far less organic inputs than men on crops that they manage. This echos results found in other studies, where men in SSA are found to be the primary household decision-markers in the allocation of agricultural inputs (Udry et al., 1995; Udry, 1996). As decision makers, men are more likely to allocate organic inputs to their own plots than their spouse's. In addition, female-headed households are less likely to own livestock. Markets for organic inputs are nearly non-existent in rural Kenya, and most organic inputs are obtained from a household's own animals. Thus, lower levels of livestock ownership in female-headed households are a significant constraint to the use of organic inputs.

[23] These included animal manure, biochar, compost (vermicompost), biochar-compost mix, and biochar-DAP mix.

Because women face greater constraints in obtaining organic inputs, when we essentially created a temporary market at their home and recommended to women that their soil results indicated that they should use organic inputs, women strongly increased their bids in hopes of making a purchase. When men however receive the same recommendation to use organic inputs, they know that they are able to reallocate organic inputs within the household and increase use on their own crops. For men, slackness may exist in the supply of organic inputs, as they can reallocate organic inputs from the woman's plot to their own, or allocate less organic resources for cooking, as building material, etc., and instead apply these inputs to agricultural uses. Women in the household, however, are often not able to make these reallocations. We believe that this intrahousehold allocation of organic inputs is likely the reason why there was no effect from the recommendation for men compared to women.

6.2.2 Difference-in-differences results: Treatment 2

Project enumerators presented participants in the second treatment group, village comparison (VC), with five charts, each for a different soil nutrient. On each chart, soil test results for each household were plotted so that an individual could compare his/her soil results with his/her village peers' results (example in Appendix A4). The charts also show the village mean of the soil results for that particular nutrient. Although the enumerator told the participant that this was a relative and not an absolute measure, no specific input recommendations were made to the participant based on the soil tests. We therefore want to test whether the participant's placement on the charts compared to his/her peers influenced the participant's demand for the auctioned agricultural inputs.

In order to estimate the overarching effect of this information, we create a variable that divides the placements in each chart into quintiles and then averages the quintile placements for each individual.[24] We then create a binary variable that is equal to 1 if the average placement is greater than the third quintile of village soil nutrient levels (3.0) (432 individuals), and 0 otherwise (452 individuals). This variable represents the broad impression that the respondent receives from viewing his/her placements on the charts. Similar to Treatment 1, those in the control group also have observations for this variable, indicating the potential treatment that was not received during the experiment.

[24] For example, if an individual is in the first quintile in his/her village for nitrogen, in the third quintile for phosphorus, second quintile for potassium, fifth quintile for sulfur, and third quintile for carbon, his average would be 2.8, meaning there overall soil nutrient level was below average (3.0).

The results from this treatment are given in Table 7. The first column shows the triple-difference estimation for all inputs that were auctioned. We see that for those who had an average soil nutrient quintile placement in their village greater than 3.0 (e.g. above average levels of soil nutrients compared to their peers), they on average decreased their bids by 13.03 KSh compared to those in the control who had an average soil nutrient quintile placement less than or equal to 3.0, significant at the 5% level. This suggests that participants who had soil nutrient levels that were better than average decreased their bids after learning their relative position. Column II shows results separated by gender. We see a surprising difference in behavior: men strongly decreased their bid when learning they had better than average soils, while women increased their bids.

Insert Table 7

The results for DAP in columns III and IV of Table 7 are insignificant and near zero, indicating that the treatment did not impact these individuals. However, the results for organic inputs in columns V and VI are similar to the overall input results in columns I and II: there is a strong decrease in bids by men when learning that their soils have better than average soil quality, while for women there is a strong increase. These results for men are statistically significant at the 1% level, while for women, they are significant at the 10% level (5% level when using the wild bootstrap method). Of course, given that this is a binary variable, the results are opposite for participants with below average soil nutrient levels: men increase their bids for organic inputs while women decrease their bids.

As described in Section 2, the limited number of economic studies using peer comparison have found that providing information about the behavior or characteristics of one's peers leads to private and public benefits. For example Goldstein, Cialdini, and Griskevicius (2008) find that providing information to hotel guests that the majority of other guests reuse towels leads to decreases in deceases in laundry costs and environmental improvements from decreased resource use. Ayres, Raseman, and Shih (2009) and Allcott (2011) find that providing information to utility customers about the energy consumption of their neighbors decreases their own energy uses. However, there is a recognition among social psychologists that there may be unintended "boomerang effects" from this kind of information. It may, for example, lead those who are consuming below average amounts of electricity to increase their electricity consumption if they learn that others are consuming more (Clee and Wicklund, 1980; Schultz et al., 2007). We believe this may be one reason for the results we see among men in the sample among organic inputs. Men, on learning that they have below average soil quality, increase their demand for organic inputs. However, if they see their soil quality is above average, they decrease their bids – reverting towards the village mean. As discussed by Cialdini (2003), we can avoid this outcome by including "injunctive norms," which suggest to the respondent what they should do as a result of this information. By also including the input recommendations, Treatment 3 includes these injunctive norms, and may be why we do not see this effect as a result.

Because the treatment caused no change in the bids for DAP, the results for organic inputs are likely influenced by the different access to resources between men and women in the household, as discussed in the results for Treatment 1. First, we must recall that unlike for Treatment 1, for participants in Treatment 2, no input recommendations were made and the participants received no additional information about organic inputs after the baseline auction. Therefore, the role that organic inputs play in restoring soil health had not been communicated to the farmers. Women, who have less access to organic inputs due to traditional intrahousehold allocation patterns, increase their bids for organic inputs on learning that their soil nutrient levels are above average, and decrease their bids if their soil nutrient levels are below average. This may be due to their lack of willingness to purchase relatively unknown inputs for use in poor soils, given their lack of knowledge as to whether these inputs will be helpful or not. Instead, they can use the cash endowment for alternative uses, such as school fees or food purchases. This is consistent with research that shows that women are more risk averse when making investment decisions than men (Niederle and Vesterlund, 2007; Croson and Gneezy, 2009). On the other hand, men have, on average, more experience with organic inputs, and thus when they see that their soil is below average are more likely to invest in organic inputs.

We next explore why bids for organic inputs changed as a result of this treatment for men but did not change when they received recommendations to use organic inputs in Treatment 1. The answer may be in the different ways that men and women respond to competition. In Treatment 1, based on soil test results, some participants were informed that they should use organic inputs to recover the health of their soils. However, these participants were not presented with a comparison to other farmers in their village. In Treatment 2, however, farmers received a comparison with their peers (though not the recommendation), which may have spurred competition. As suggested in the literature on this subject (Bateup et al., 2002; Croson and Gneezy, 2009), men are sometimes argued to possess a more competitive nature when it comes to economic decisions, whether due to societal structures, biology, or other factors. Although this is a speculative matter, the significant change in bids among men that we see for organic inputs in Treatment 2 which is absent in Treatment 1 might be due to this factor.

6.2.3 Difference-in-differences results: Treatment 3

Treatment 3 combines the last two treatments, and provides the randomly assigned participants with input recommendations based on their individual soil test results, as well as showing them the charts that indicate their relative soil nutrient levels compared to their anonymized village peers. For all participants in this treatment group, the order of information was the same – first the participant received the soil test results and input recommendations, and then the individual was shown the charts that showed the relative position of his/her soil compared to others in the village. In Table 8, we present the results in the same manner as Treatment 1, and show the effects of the input recommendations, conditional on having also seen the village comparison charts.[25]

Insert Table 8

We can see that the direction of the results are similar to Treatment 1: the effect of the recommendation to use DAP is positive across the full sample and for each gender, and the effect of the organic input recommendation is positive for the full sample, near zero for men, and positive for women. However, the results lack the statistical significance that we found for Treatment 1. Only the effect of the information treatment on average bids for DAP in the full sample (43.38 KSh) is statistically significant.

This outcome is a bit surprising; we expected that this treatment might have the strongest effect as the participants received the most information and the enumerator spent the most time discussing the results. However, there are several reasons why this may not be the case. First, the combination of input recommendations and comparisons with one's peers may have influenced the participants in different directions. For example, if an organic input was recommended to a female participant, and she also had poor soil health compared to her peers, the results from the other treatment groups suggest that these effects would have influenced her in different directions. A recommendation to use organic inputs would tend to increase her bid

[25]We also looked at the results in a similar way as the results from Treatment 2. None of the estimated coefficients are statistically significant. These results are not shown in this version of the paper, but are available upon request.

according to the results from treatment 1, but the poor quality of her soil would likely decrease her bid, according to the results from Treatment 2. This therefore could have attenuated the effect that we see on Table 8 for this treatment.

The volume of information presented to the participant may also have attenuated the impact. While each information treatment separately took about ten minutes, combining them in Treatment 3 increased the time spent providing the information to about twenty minutes. The relatively long amount of time spent on this treatment compared to the others may have caused some participants to lose focus and their bids may have been less accurate.

Finally, due to how the random assignment was implemented, Treatment 3 contained the fewest number of participants. As discussed in Section 5.2, the tablet computer randomly assigned a treatment to a participant in between the auction rounds. This prevented any unintentional bias that may have risen from the enumerator knowing the participant's treatment beforehand. However, the disadvantages to this method is that the treatment groups have uneven numbers of participants. Treatment 3 had the fewest participants in total, especially among men. Therefore, due to the lower statistical power in these estimations compared to the others, the coefficient were estimated less precisely, and this may also have led to the lack of significant results for this treatment.

7 Discussion and implications

In SSA, small-scale farmers often suffer from poor crop yields due to low soil nutrient levels on their farms. This can lead to a downward cycle in living standards, in which farmers are unable to invest in inputs for their fields, leading to lower yields, lower incomes, and less investment in inputs the next season. Even if farmers do invest in their fields, they often do not have sufficient information to make profit-maximizing decisions. They may know that their farms have poor soil health, but are not able to discern whether the soil is lacking in nitrogen, carbon, is acidic, or has other deficiencies. Due to the complexity of tropical soils, input prescriptions vary depending on the nutrient composition of the soil. Thus, even if a farmer invests heavily in inorganic fertilizers like DAP (not uncommon in this area), the fertilizers may have a limited impact on yield improvement due to low carbon levels or high acidity. Furthermore, DAP use can lead to further decreases in their soil quality through acidification when used without liming or when not complemented with organic inputs like animal manure or crop residues (Vanlauwe and Giller, 2006).

This study has sought to test whether providing small-scale farmers with soil test results and information such as personalized agricultural input recommendations will affect their behavior and lead to improved optimization of their agricultural input choices. The study took soil samples from the randomly selected farms of 884 individuals in western Kenya, analyzed them, and returned to the households with farm specific test results. We divided the sample into three information treatment groups: those who received farm specific input recommendations based on the test results, those who received a comparison of the soil nutrient levels on their farms with their anonymized peers, and those who received both of these treatments combined. To measure the impact of the information treatments, we used a two-round experimental auction methodology after Becker, DeGroot, and Marschak (1964) and compared these treatment groups to a control group. We estimate results using both a mixed model that includes random coefficient estimates and difference-in-differences.

Using a mixed model, we test for differences in the dispersion of the change in auction bids across rounds and between individuals. Overall, we find that the between-individual dispersion is greater for those in the treatment groups compared to the control, suggesting that the treatments had a greater influence on behavior by causing the change in bids between individuals to have more variability. However, the results differed sharply between men and women. We found that the difference in the dispersion in bids between treatments and control was large for men, but did not exist among women. We believe this is likely caused by the lower rate of input use among women in the sample compared tomen. Less experience using these inputs may have led to less ability to construct preferences in the initial bids of women, causing them to be more likely than men to change their minds between auction rounds.

To get a more precise understanding of the impacts of the type of information received with each treatment, we use triple-difference estimations (differences in auction round, treatment-control, and information type). For Treatment 1, we specifically look at the difference between those who receive a particular input recommendation (such as those advised to use an organic input) and those who do not. Overall, we find a statistically significant and economically large effect of the change in WTP for DAP fertilizer between those who are recommended a nitrogen input in the treatment group and those in the counterfactual control group. For organic inputs, we find no effect. However, when we add a fourth difference to the estimation (between men and women), we find a surprising result: for men, there is no effect of the recommendation to use organic inputs, but for women, there is a large and statistically significant effect. Women in the treatment group who are recommended that an organic input (e.g. animal manure) be used to recover soil health on average bid 32.47 KSh higher than those in the counterfactual control group.

We believe that the different impact between men and women from the organic input recommendation is connected to the lack of access to resources among women in the household. As we will explore further in forthcoming versions of this paper, women in our sample on average are less likely to use organic inputs on crops that they manage. This is likely related to the role of men in the intrahousehold allocation of resources. Other research in SSA has found that men tend to allocate household agricultural resources, such as animal manure, to plots that they manage rather than to female-managed plots (Udry et al., 1995; Udry, 1996). We also find that women-headed households have significantly lower livestock holdings than in male-headed households. Because a market for organic inputs is nearly nonexistent in western Kenya, most farmers obtain their organic inputs from their own livestock. Because women are often not able to obtain organic inputs through intrahousehold allocation or through livestock ownership, when the survey enumerators recommended using organic inputs, they increased their bids significantly in the hope of purchasing the input through the temporary market created by the auction mechanism. Men on the other hand, when recommended that they use organic inputs, knew that they could reallocate existing organic inputs already on their farm for use on their own crops, and therefore the information did not affect their bidding behavior.

In Treatment 2, individuals compared their own soil quality levels to that of their peers (without hearing any input recommendations, and again find that the results depend greatly on gender. For men, if their soil quality is above average, they tend to decrease their bids for organic inputs, while if they are below the average they increase them. For women the opposite is true; they decrease their demand for organic inputs if they have below average soil quality, but increase their demand when their soil quality is above average.

We find few significant results from Treatment 3, where both the above treatments were given to individuals. This may be due to several reasons, including that the effects of the treatments affected the individuals in offsetting directions, that the treatment took too long and caused the participants to lose focus, and/or because the sample size was the smallest of the three treatments and we lack the statistical power to precisely estimate the effects.

The results from Treatments 2 and 3 also inform us about the potential and limitations of using peer comparisons to influence behavior. The very limited number of economic studies that have tested the effects of peer comparison on behavior (Goldstein, Cialdini, and Griskevicius, 2008; Ayres, Raseman, and Shih, 2009; Allcott, 2011) show that they lead to private and public benefits. However, it appears that showing the peer comparisons alone (Treatment 2) leads to a "boomerang effect" for men, as those with soil quality below-average increase their demand for organic inputs, but those with above-average soil quality decrease their demand and revert towards the mean. Treatment 3 seems to have reduced the boomerang effect, decreasing the magnitude of the effects to the point where they are not statistically significant. For women, the opposite of the boomerang effect seems to occur; for those above the average, they increase their bids for organic inputs, and for those below the average, they decrease them. We believe that because women are usually more risk averse than men (Niederle and Vesterlund, 2007; Croson and Gneezy, 2009), they are less inclined to invest in inputs for relatively poor soils. Men are less risk averse and, according to Niederle and Vesterlund (2007) and Croson and Gneezy (2009), among others, are more economically competitive than women. This may have contributed to men increasing their bids for organic inputs when they have relatively poor soil compared to their peers, but not when given an explicit recommendation without the peer comparison as in Treatment 1.

The results from the difference-in-differences estimations, particularly those for Treatment 1, are especially notable given the results from the mixed model estimations. In the mixed model estimation results, we found that between-individual variability for women in the control group to be surprisingly high. The significant results in difference-in-differences estimations for women are evident despite this high degree of statistical noise that comes from the control group, suggesting the substantial impact of the treatments within the sample.

Throughout this research, we attempt to reduce the information constraint that farmers face in optimizing their agricultural input choices. However, farmers face several other constraints, including the lack of resources available to invest in agricultural inputs, lack of financial liquidity, and high opportunity costs of domestically available inputs such as animal manure. By providing a cash endowment to participants through the experimental auction design, we eliminate any liquidity constraint and directly provide resources for the bidding. However, during the explanation of the auction method, it was made clear to participants that they could use the cash endowment for other purposes outside of the auction, thus providing us with incentive-compatible estimates. Therefore, these results should be interpreted as those that would arise given access to liquidity. Other research, such as the well-known Duflo, Kremer, and Robinson (2011) study, seeks to help farmers address the liquidity constraints that arise from the timing of fertilizer purchasing. This study therefore attempts to address one important constraint, accurate information, but cannot adequately address all constraints simultaneously.

We should also note the possibility of the Hawthorne Effect potentially influencing our results. Participants may bid the way that they think that we as the project implementers want them to bid, rather than what their true preferences might reveal, or their bidding may be influenced by how much they trust the implementing institution. While it is not possible to completely disregard the possibility of this effect, we believe the design of the experimental auction mitigates against it. Because we are using real money, and the fact that we emphasize to the participants that it is their money to do with it as they wish, we believe this creates an economic incentive to behave according to their own preferences rather than in a way they think the implementer wishes. Moreover, because most of the participants had never heard of the implementing organization (IITA), and 87% of households do not have any contact with NGOs, we believe that it is unlikely that the respondents had strong feelings of trust in either direction that would affect their behavior.

The results overall point importantly to the promises of soil testing to help developing world farmers optimize their agricultural input allocations. Input recommendations can improve farmer yields by indicating what inputs would be most effective at improving soil health, and which are less important or should be avoided. A farmer with acidic soil and low organic matter, for example, would be advised to focus on increasing compost and animal manure use and avoid DAP. If this farmer was already using large amounts of DAP, he/she could save those funds and instead use them to either purchase organic inputs or purchase livestock, which will allow domestic production of the needed inputs. In forthcoming versions of this paper, we will report the results of a cost-benefit and welfare analysis of these soil tests that show the potential for significant increases in farmer welfare from their use.

Our results also suggest that development programs should increase their targeting of women, especially with regard to livestock access. Because it appears that men tend to allocate their household's resources, including organic resources like animal manure, for use on their own plots, women do not have access to the same levels of organic resources necessary for soil health as do men. Programs that focus on increasing ownership of livestock among women will help to give women access to animal manure and thus increase soil health and crop yields on plots that they manage.

Given these results, it appears likely that widespread soil testing may be an effective way of increasing agricultural input optimization among farmers. Rather than subsidization, which is costly to the government, generates distortions in the market, and can cause farmers to over-allocate their resources towards ineffective or deleterious inputs (such as DAP on acidified soils), governments could choose to help implement soil testing programs similar to the one implemented in this research. Work by Fabregas et al. (2014) in western Kenya show that farmers are willing to pay for soil test results, potentially making wide-spread soil testing using the Soildoc system self-sustaining.

Extensive rural poverty and food insecurity has remained a persistent problem in SSA and much of the developing world. A major cause is soil degradation and resulting poor crop yields that prevents accumulation of assets. Farmer optimization of agricultural input use can improve soil health and move farmers out of a resource poverty trap. Organic agricultural inputs are generally underused in SSA yet have particular potential for improving crop yields, especially in areas with highly carbon-degraded soils. However, it is difficult for farmers to form accurate measures of their soil nutrient levels to determine an optimal match with agricultural inputs. Coupled with liquidity constraints, uncertainty regarding appropriate inputs for a particular farmer's soil nutrients and soil type limits the adoption and intensity of use of often necessary soil amendments. Soil testing may therefore be a key tool in optimizing the farmer's agricultural input choices, reversing soil degradation, and improving farmer livelihoods in rural SSA.

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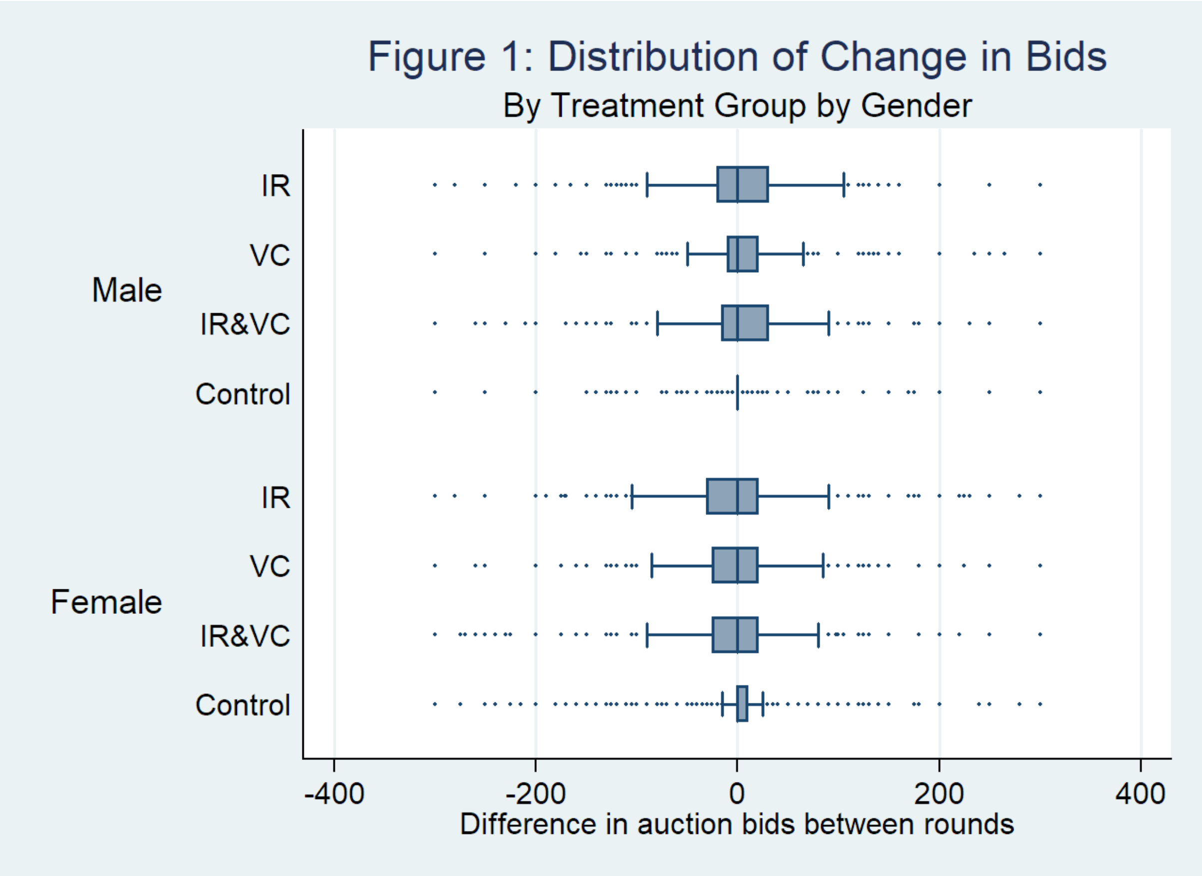


Figure 1: Distribution of Change in Bids
By Treatment Group by Gender
Male
IR
VC
IR&VC
Control
Female
IR
VC
IR&VC
Control
-400
-200
0
200
400
Difference in auction bids between rounds

Table 1: Soil Fertility in Western Kenya*

Indicator	Threshold Value**	Percent of sample farms below threshold (N=559†)
Nitrate	40mg NO_3 per kg soil^{-1}	95.7
Phosphorus	1mg PO_4^3 per kg soil^{-1}	96.1
Potassium	60mg K per kg soil^{-1}	73.4
Sulfate	20mg SO_4^2 per kg soil^{-1}	80.9
Active Carbon	500mg Active C per kg soil^{-1}	66.6
pH	5.5	18.4

*Kakamega, Bungoma, and Busia counties. See Appendix A1 for a map of sample village locations. **Thresholds developed by Weill and Palm. †The number of households in this sample greater than elsewhere in paper due to sample attrition between soil sample collection and household interviews.

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Individual (n=884)				
Age	48.29	16.09	19.00	109.00*
Years of Education	7.95	3.80	0.00	26.00**
Yes=1:				
Basic math ability***	0.56	0.50	0.00	1.00
Female	0.58	0.49	0.00	1.00
Widow/er	0.14	0.35	0.00	1.00
Primary occupation is farmer	0.88	0.33	0.00	1.00
Anglican	0.29	0.45	0.00	1.00
Catholic	0.17	0.37	0.00	1.00
Pentecostal	0.42	0.49	0.00	1.00
Bukusu subtribe	0.37	0.48	0.00	1.00
Luhya tribe (except Bukusu)	0.31	0.46	0.00	1.00
Iteso tribe	0.29	0.45	0.00	1.00
Household (n=548)				
Household size†	5.29	3.27	0.00	40.00
Total land area (arable acres)	1.06	1.06	0.02	8.87
Household spending on food per week (KSh)‡	1228.52	1773.12	0.00	21000.00
Yes=1:				
Household head is male	0.55	0.50	0.00	1.00
Organic inputs (within past two seasons)	0.45	0.50	0.00	1.00
Inorganic inputs (within past two seasons)	0.88	0.33	0.00	1.00
No inputs (within past two seasons)	0.07	0.25	0.00	1.00
NGO contact	0.13	0.34	0.00	1.00
River as water source	0.43	0.50	0.00	1.00
Electricity (grid)	0.13	0.33	0.00	1.00
Solar panels	0.29	0.45	0.00	1.00
Metal roof	0.87	0.33	0.00	1.00
Mud walls	0.77	0.42	0.00	1.00
Earth/Mud floor	0.72	0.45	0.00	1.00
Polygamous household	0.10	0.30	0.00	1.00
Own cow(s)	0.63	0.48	0.00	1.00
Village (n=17)				
Individuals (interviewed per village)	52.00	13.91	38.00	97.00
Households (sampled per village)	32.24	8.39	21.00	57.00

*There was one woman who claimed she was 109 years old. **The sample included a couple of individuals who were university professors and had PhDs. ***Was able to do a basic multiplication problem. †Defined as the number of individuals who spent the night at that dwelling last night. ‡1 USD was approximately equal to 102 KSh at the time of the survey.

Table 3: Sample Size by Group*

Treatment	Women	Men	Total
T1: IR	137	96	233
T2: VC	117	101	218
T3: IR & VC	128	77	205
Control	129	99	228
Total	511	373	884

*Uneven distribution among treatments due to random assignment by tablet computer at time of auction.

Table 4: Distribution Statistics by Treatment and Gender

Overall

Treatment	Mean	Std. Dev	N
IR	0.09	78.91	2739
VC	1.04	75.50	2554
IR&VC	-0.35	79.97	2413
Control	-1.87	59.75	2700

Men

Treatment	Mean	Std. Dev	N
IR	3.99	80.36	1134
VC	3.25	71.47	1186
IR&VC	5.80	80.89	903
Control	-5.19	46.23	1171

Women

Treatment	Mean	Std. Dev	N
IR	-2.65	77.77	1605
VC	-0.88	78.81	1368
IR&VC	-4.03	79.21	1510
Control	0.67	68.22	1529

Results using trimmed sample as described in Section 5.2

Table 5: Mixed Model Estimations

	$\bar{u}_j$: **Mean Estimates**		
	Overall	**Men**	**Women**
First Bid	-0.216***	-0.184***	-0.239***
	(0.0172)	(0.0233)	(0.0178)
T1: IR	85.96***	175.0***	-43.07
	(30.96)	(48.07)	(37.07)
T2: VC	88.22***	172.7***	-38.46
	(30.74)	(46.52)	(36.81)
T3: IR & VC	84.08***	169.7***	-42.85
	(30.15)	(46.73)	(36.03)
Control	83.92***	165.3***	-39.74
	(31.67)	(47.49)	(37.84)
Individual, HH, farm covariates	√	√	√
F.E. (enumerator, month, village)	√	√	√
	λ_j: **Standard Dev. Estimates**		
	Overall	**Men**	**Women**
T1: IR	28.40***	29.17***	26.93***
	(3.420)	(4.020)	(3.567)
T2: VC	26.31***	25.87***	24.54***
	(3.428)	(5.400)	(3.816)
T3: IR & VC	23.54***	25.02***	18.29***
	(2.518)	(4.004)	(3.550)
Control	20.01***	9.051***	25.55***
	(2.111)	(4.977)	(2.385)
Residual	64.00***	61.27***	65.75***
	(2.235)	(2.597)	(2.236)
N	10406	4394	6012

Clustered standard errors (at village level) in parenthesis. Individual, household, and farm characteristics include exogenous variables such as age, education, farm area, asset index, years in village, and tribe. ***p<0.01, **p<0.05, *p<0.1.

Table 6: Difference-in-Differences Results: Treatment 1

		DAP		Organic inputs	
		I	II	III	IV
Use N × treatment 1 × time	Treatment effect	60.820***	49.325***		
	SE	9.029	14.428		
	Cluster p-value	0.000	0.004		
	WB p-value	0.000	0.000		
Use N × treatment 1 × time × female	Treatment effect		20.392		
	SE		21.889		
	Cluster p-value		0.365		
	WB p-value		0.352		
Use O × treatment 1 × time	Treatment effect			15.934*	-3.708
	SE			8.235	13.951
	Cluster p-value			0.071	0.794
	WB p-value			0.060	0.796
Use O × treatment 1 × time × female	Treatment effect				34.070**
	SE				15.999
	Cluster p-value				0.049
	WB p-value				0.092
Covariates		Yes	Yes	Yes	Yes
F.E. (Village, enumerator, month, input, input × time)		Yes	Yes	Yes	Yes
N		1824	1824	9008	9008
R^2		0.669	0.670	0.506	0.506

Standard errors (SE) are clustered at the village level. Wild bootstrap p-values are included to correct for small sample size (17) with 1000 repetitions. ***p<0.01, **p<0.05, *p<0.1.

Table 7: Difference-in-Differences Results: Treatment 2

		All inputs		**DAP**		**Organic inputs**	
		I	II	III	IV	V	VI
Avg Quintile>3 × treatment 2 × time	Treatment effect	-13.026**	-23.889***	4.591	-0.146	-16.575***	-28.729***
	SE	5.222	6.946	6.849	9.580	5.249	7.769
	Cluster p-value	0.024	0.003	0.512	0.988	0.006	0.002
	WB p-value	0.016	0.004	0.500	1.000	0.008	0.008
Avg Quintile>3 × treatment 2 × time × female	Treatment effect		19.799*		10.390		21.720*
	SE		10.048		19.363		10.923
	Cluster p-value		0.066		0.599		0.064
	WB p-value		0.048		0.652		0.076
Covariates		Yes	Yes	Yes	Yes	Yes	Yes
F.E. (Village, enumerator, month, input, input × time)		Yes	Yes	Yes	Yes	Yes	Yes
N		10509	10509	1766	1766	8743	8743
R^2		0.508	0.509	0.657	0.648	0.475	0.474

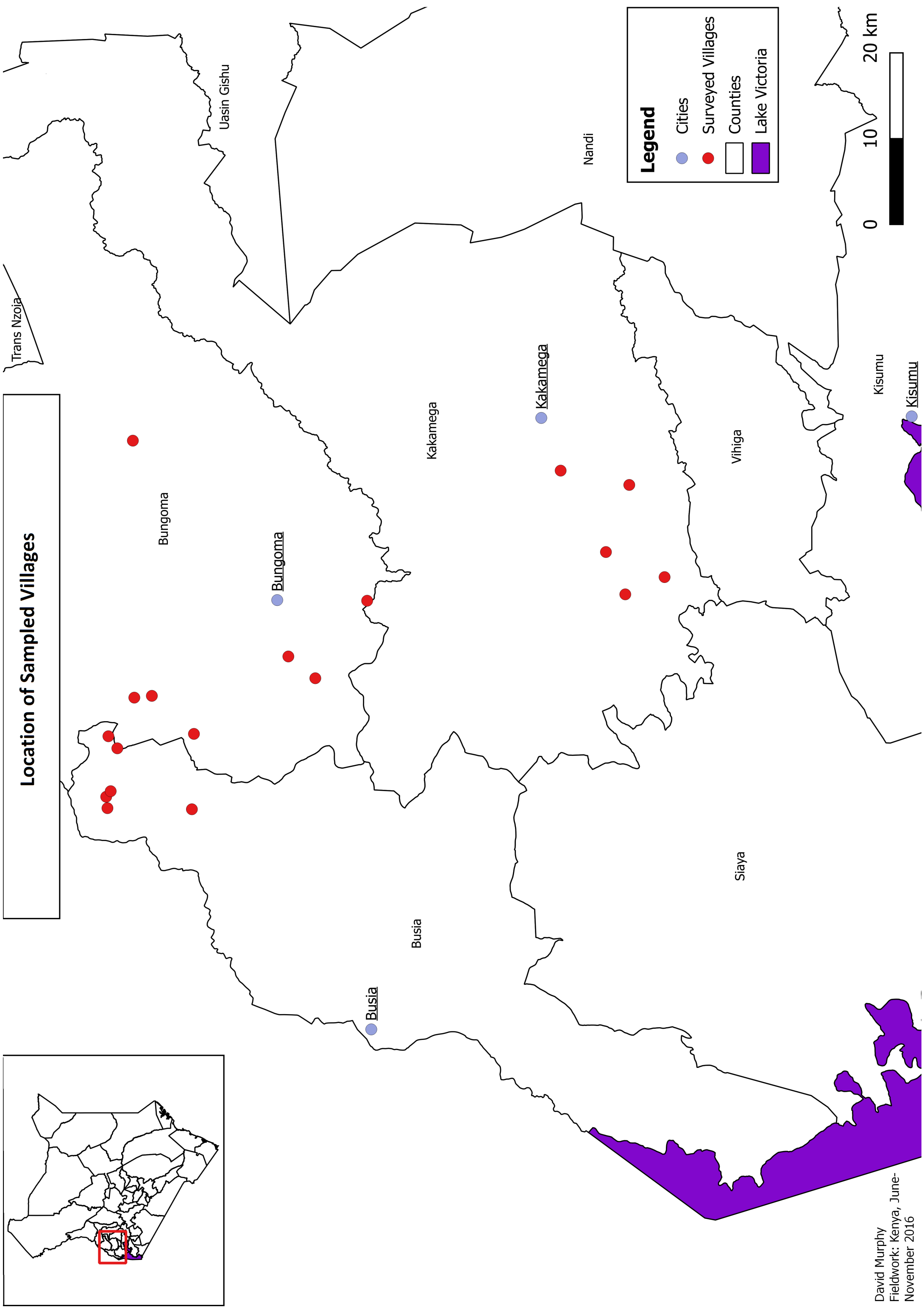
Standard errors (SE) are clustered at the village level. Wild bootstrap p-values are included to correct for small sample size (17) with 1000 repetitions. ***p<0.01, **p<0.05, *p<0.1.

Table 8: Difference-in-Differences Results: Treatment 3

		DAP		Organic inputs	
		I	II	III	IV
Use N × treatment 3 × time	Treatment effect	43.381***	21.977		
	SE	9.371	17.506		
	Cluster p-value	0.000	0.227		
	WB p-value	0.000	0.292		
Use N × treatment 3 × time × female	Treatment effect		35.473		
	SE		29.016		
	Cluster p-value		0.239		
	WB p-value		0.304		
Use O × treatment 3× time	Treatment effect			8.919	-2.515
	SE			6.112	11.984
	Cluster p-value			0.164	0.836
	WB p-value			0.148	0.976
Use O × treatment 3 × time × female	Treatment effect				19.550
	SE				12.567
	Cluster p-value				0.139
	WB p-value				0.160
Covariates		Yes	Yes	Yes	Yes
Fixed effects (Village, enumerator, month, input, input × time)		Yes	Yes	Yes	Yes
N		1722	1722	8465	8465
R^2		0.662	0.664	0.500	0.501

Standard errors (SE) are clustered at the village level. Wild bootstrap p-values are included to correct for small sample size (17) with 1000 repetitions. ***p<0.01, **p<0.05, *p<0.1.

Appendix A1: Project area



Appendix A2: Soildoc soil testing system information

SoilDoc offers a diagnostic kit and management system for the use in 'plot-specific' analysis of soil properties that are related to fertility and nutrient availability, and uses geo-referencing to generate soil maps. The analysis of N, P, active C, sulfur, and aggregate stability offered by the SoilDoc kit has comparable accuracy as standard laboratories. Other advantages of the SoilDoc system are that 1) it can be deployed anywhere, 2) it offers low cost per test, 3) it has high accuracy, and 4) gives fast diagnosis of the soil fertility status. One trained person can complete full SoilDoc analysis for 40 and 60 samples per week (2000 samples per year). Including the chemicals, other consumables, and replacement of all instruments over a three year period, the cost for one full suite of tests remains under 3 USD with less than 1,000 samples per year, and is close to 2 USD with 2,000 samples per year. The pay-grade a trained technician in Kenya is about 10,000 USD per year. Thus, not including costs for transport or space, is about 7 USD per sample. Overall, soil analysis by the SoilDoc system costs significantly less than at any research or commercial lab. At the moment, research efforts are being undertaken to validate and improve the fertilizer recommendations for maize crops through meta-analysis of trials. So far, a single threshold value is being used to establish whether fertilizers should be used or not, but more comprehensive models of SoilDoc tests are being developed to give more detailed recommendations.

In this research project, soil samples were taken two to three months before the onset of rains by trained staff, making a composite from five evenly staggered positions in a field where farmers planned to grow maize in the subsequent growing season. The soil was thoroughly mixed by hand and a 250g subsample was carried to the field lab. Before analysis, the soil samples were placed in solar driers for 4 days and manually sieved over 2mm. The pH of soils (a measure of acidity) and electric conductivity (an indicator for the total amount of exchangeable nutrients in soils) were measured in a solution of 10g soil and 20mL water using electrodes. These soil solutions were further subjected to calcium chloride extraction (0.01 mol salt per liter) and then filtered over paper for analysis. Nitrate and potassium in soil extracts were measured with ion-specific electrodes that were calibrated against two standard solutions each day of measurement. Phosphorus and sulfate-S in soil extracts were analyzed through reactions with molybdate and barium chloride that were measured with pocket photo-spectrometers, checked against one standard solution each day. Active C in soils was analyzed through permanganate digestion of 2.5g subsamples, after which supernatant was measured against a three point calibration curve using a pocket photo-spectrometer. Samples were processed in batches of 15 samples per day plus one reference soil that was measured in all batches. All of the analysis were carried out with drinking water from local sources, and blank water corrections were made in calculations of soil nutrient contents for each batch separately. The values of nutrient content were disaggregated in multiple ranges related to soil fertility, whereas fertilizer recommendations were binary, i.e. advising to apply when nutrient levels were below moderate values listed below in Table A2.

Table A2: Soildoc Nutrient Thresholds

Parameter	Extremely Low	Very Low	Low	Moderate (or Optimum pH)	High	Very High
Nitrate mg NO_3 per kg soil^{-1}	$x < 4.5$	$4.5 \leq x < 5$	$5 \leq x < 5.5$	$5.5 \leq x < 6$	$6 \leq x < 6.5$	$x \geq 6.5$
Phosphate mg PO_4^3 per kg soil^{-1}	$x < 10$	$10 \leq x < 20$	$20 \leq x < 40$	$40 \leq x < 60$	$60 \leq x < 80$	$x \geq 80$
Potassium mg K per kg soil^{-1}	$x < 15$	$15 \leq x < 30$	$30 \leq x < 60$	$60 \leq x < 90$	$90 \leq x < 120$	$x \geq 120$
Sulfate mg SO_4^2 per kg soil^{-1}	$x < 5$	$5 \leq x < 10$	$10 \leq x < 20$	$20 \leq x < 30$	$30 \leq x < 40$	$x \geq 40$
Active Carbon mg Active C per kg soil^{-1}	$x < 200$	$200 \leq x < 350$	$350 \leq x < 500$	$500 \leq x < 650$	$650 \leq x < 800$	$x \geq 800$
pH	$x < 4.5$	$4.5 \leq x < 5$	$5 \leq x < 5.5$	$5.5 \leq x < 6$	$6 \leq x < 6.5$	$x \geq 6.5$

Appendix A3: Auction scripts

English

Practice Auction Script We will now play a market game. Here is 70 shillings. This 70 shillings is yours to keep and do as you wish. You can use the money in the game, but you are not required to. We are interested in finding out how much you would pay for several items. We have a vanilla cupcake, chocolate cupcake, some cookies, and a 50 shilling note. We will ask you to tell us the maximum price you are willing to pay for each of these items. After you have told how much you would pay for each item, one item will be selected at random by the computer. A price will then be randomly chosen for that item by the computer. If the price you tell me is higher than the random price, you will pay the random price that was chosen and I will give you the item. If the random price is lower than the maximum you are willing to pay, you will keep all the money I have given you and I will keep the item. Under this procedure, it is in your best interest to tell me exactly the maximum you are willing to pay for each item; no more and no less. If you tell me a price that is higher than the maximum you actually want to pay for an item and it is chosen, you will be required to pay this price if it is randomly chosen. If the price you tell me is lower than the maximum you would pay for an item, then if a good price is chosen by the computer but your price is lower, you will not be allowed to buy the item at the good price even if you want to. Do you understand how this game works?

Baseline Auction Script We will now play the same market game for agricultural inputs. Here is 700 shillings. This 700 shillings is yours to keep and do as you wish. You can use the money in the game, but are not required to. We are now interested in finding out how much you would pay for several agricultural items. The game procedure will be exactly the same as for the food items. Under this procedure, it is in your best interest to tell me exactly the maximum you are willing to pay for each item; no more and no less. If you tell me a price that is higher than the maximum you actually want to pay for an item and it is chosen, you will be required to pay this price if it is randomly chosen. If the price you tell me is lower than the maximum you would pay for an item, then if a good price is chosen by the computer but your price is lower, you will not be allowed to buy the item at the good price even if you want to. Do you understand how this game works?

Second Auction Script Now that you have heard the (soil test results), we will play the same market game again. After this round, either this round or your previous round will be chosen as the binding round. One item will be randomly selected from either this round or the previous round, and a random price will be chosen for it by the computer. It is in your best interest to tell me exactly the maximum you are willing to pay for each item; no more and no less. If you tell me a price that is higher than the maximum you actually want to pay for an item and it is chosen, you will be required to pay this price if it is randomly chosen. If the price you tell me is lower than the maximum you would pay for an item, then if a good price is chosen by the computer but your price is lower, you will not be allowed to buy the item at the good price even if you want to.

Agricultural Input Explanation "Biochar" is a type of charcoal that is produced from left-over plant material of field crops on farm like maize cobs and stovers, rice husks and haulms, sugarcane bagasse, coconut shells, and others. If applied to soil at the correct rate, biochar helps to improve crop production by increasing the uptake of fertilizers, manure and water. "Vermicompost" is the end-product of the breakdown of organic matter by an earthworm, also called worm castings. It is compost produced using earthworms. If applied to the soil in the correct rate vermicompost will improve crop production because it contains substantial amounts of nutrients, has a large water holding capacity and enriches the soil with micro-organisms.

Kiswahili

Zoezi la mnada wa nakala Sasa tutacheza mchezo wa soko. Chukua hii shillingi 70. Hii shilling 70 ni yako na unaweza kufanya nalo kile unachotaka. Unaweza tumia pesa hii kwa mchezo huu, na hiyo pia sio lazima. Tungependa kujua ni kiasi gani ya thamani gani utalipia vitu mbali mbali. Tunalo (queen cakes) aina ya vanilla, chakoleti , kuki zingine , na shilling 50. Tutakuuliza utuambie kile bei ya juu zaidi unaweza lipa kununua kila mmoja ya hivi vitu. Baada ya kutuambia kile malipo unaweza lipa kwa kila bidhaa , bidhaa moja itachaguliwa ki nasibu kupitia njia ya tarakilishi . Bei ya bidhaa hiyo vile vile itachaguliwa ki nasibu kupitia njia ya tarakilishi. Kama bei ulichoniambia ni zaidi ya kile bei kilichochaguliwa ki nasibu na tarakilishi, utalipa kile bei kilichochaguliwa ki nasibu na tarakilishi na nitakupatia bidhaa hiyo. Kama bei ilichochaguliwa ki nasibu ni chini zaidi ya ile bei ya juu uliyosema unaweza lipa kununua bidhaa, utabaki na pesa zote nilichokupatia na mimi nitabaki na bidhaa zangu. Katika hii utaratibu ni kwa mvuto yako kuniambia bei ya juu kamili na halisi unaweza lipia kununua kila bidhaa; bila kuweka bei ya juu zaidi au ya chini sana. Ukiniambia hile bei ya juu zaidi ya hile wewe hasa ungependa kuweka kama bei yako ya juu ya kununua bidhaa na bidhaa ichaguliwe ki nasibu, itabidii ulipe hii bei kununua bidhaa hiyo. Kama bei ulichoniambia ni chini zaidi ya bei wewe hasa ungependa kulipa kama kiwango cha juu basi utalipia bidhaa, Kisha kama bei imechaguliwa ki nasibu na bei yako ni chini, hutakubaliwa kununua bidhaa kwa bei nafuu hata ukiwa unahitaji. Je' unaelewa jinsi huu mchezo unachezwa?

Msingi wa mnada wa nakala Sasa tutacheza huu mchezo ya soko tena. Kutumia hii ni shilingi 700. Hii shilingi 700 ni yako ya kuweka na kutumia utakavyo. Unaweza kumia hii pesa kati huu mchezo. Lakini sio lazima. Sasa tungependa kujua ni kwa thamani gani utalipia pembejeo kadhaa. Utaratibu ya mchezo huu utafanana kabisa na ule wa vitu vya kula hapo . Katika huu utaratibu ni kwa mvuto wako kuniambia bei ya juu kamili na halisi unaweza lipia kununua kila bidhaa; bila kuweka bei ya juu zaidi au ya chini sana. Ukiniambia hile bei ya juu zaidi ya ile wewe hasa ungependa kuweka kama bei yako ya juu ya kununua bidhaa na bidhaa mabei wewe hasa ungependa kulipa kama kiwango cha juu basi utalipia bidhaa, kisha ikiwa bei imechaguliwa ki nasibu na bei yako ni chini, hutakubaliwa kununua bidhaa kwa bei nafuu hata ikiwa unahitaji. Je' unaelewa jinsi huu mchezo unachezwa?

Udongo ya Mnada Kwa vile umesikia kuhusu (utafiti ya udongo) Tutacheza michezo ya hawali tena . Baada ya huu msururu, huu msuru au msururu ya hapo hawali itachaguliwa kuwa msururu wa mwisho. Bidhaa moja itachaguliwa ki nasibu kati huu msururu au musururu ya hapo hawali, na kwa njia ya kinasibu bei itachaguliwa na tarakilishi .Katika hii utaratibu ni kwa mvuto wako kuniambia bei ya juu kamili na halisi unaweza lipa kununua kila bidhaa; bila kuweka bei ya juu zaidi au ya chini sana. Ukiniambia hile bei ya juu zaidi ya hile wewe hasa ungependa kuweka kama bei yako ya juu ya kununua bidhaa na bidhaa ichaguliwe kinasibu, itabidii ulipe hii bei kununua bidhaa hiyo. Kama bei ulichoniambia ni chini zaidi ya bei wewe hasa ungependa kulipa kama kiwango cha juu basi utalipia bidhaa, Kisha ikiwa bei imechaguliwa kinasibu na bei yako ni chini, hutakubaliwa kununua bidhaa kwa bei nafuu hata ikiwa unahitaji.

Maelezo ya mbolea ya kilimo "Biochar" "Makaa ya shamba" ni aina ya makaa ambaye inatengenezwa kutoka kwenye mabaki ya mimeya kama msogoro, na vijiti za mahindi, bagasse ya miwa, mabakio ya nazi na zinginezo. Ikimwagwa kwenye udongo shambani kwa kiwango inayo faa, Makaa ya shamba (Biochar) usaidia kuwepo mazao mazuri kwa kuongeza uwepo wa madini, mbolea ya wanyama na maji. "Vermicompost" ni bidhaa inayo totakana na kinyesi ya earthworm (mniambo). Ikimwagwa kwenye udongo shambani kwa kiwango inayo faa mbolea ya vermicompost itaongeza mazao kwa sababu ina madini mingi sana, na pia inashikilia unyevu kwa kiwango kikubwa na vile vile inaoneza vihini bora kwenye udongo.

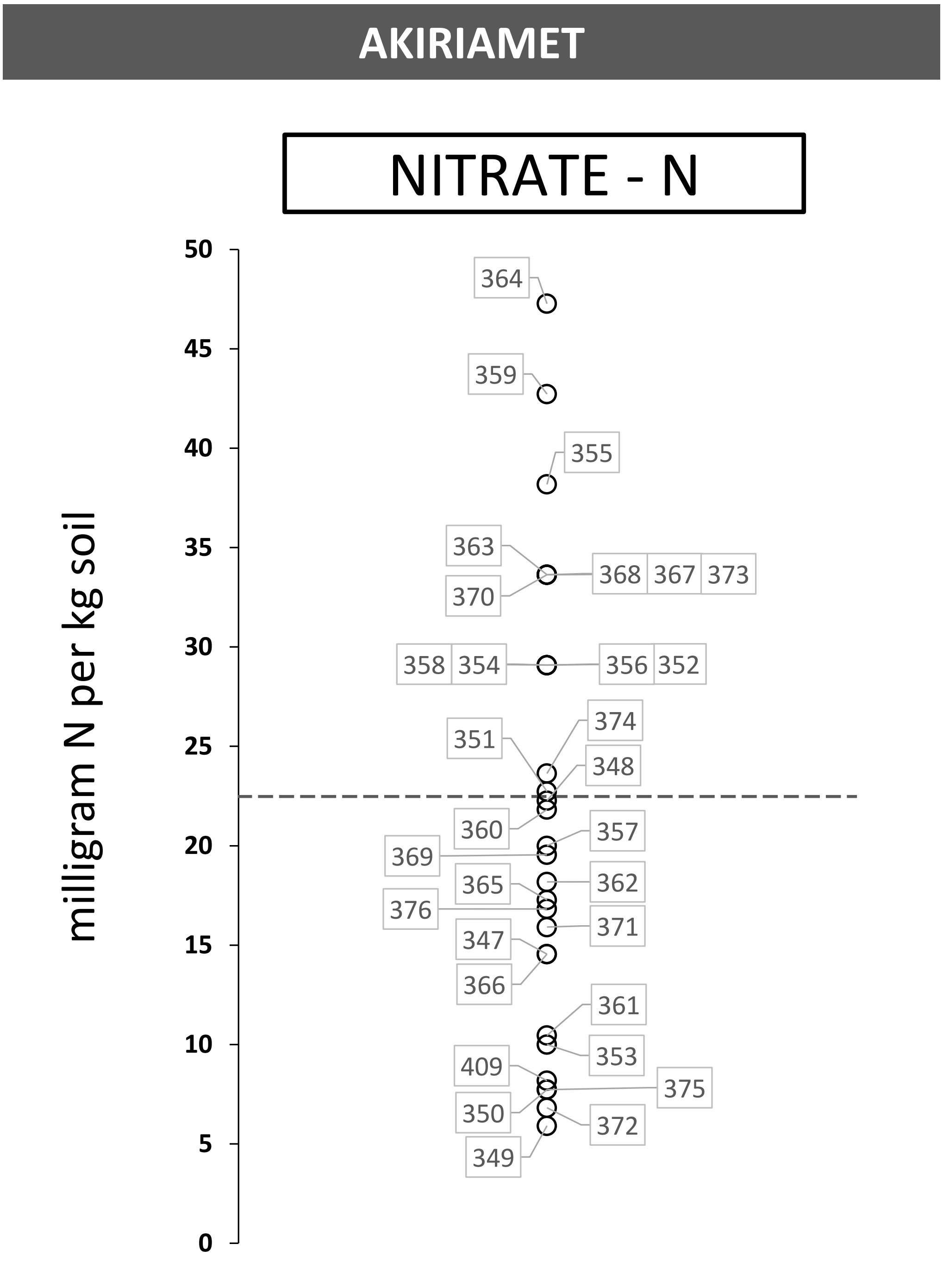
Appendix A4: Experimental auction supplements

Sample Soil test report

SAMPLE CODE	Village	Farmer	Acidity (pH)	Acidity Level	Soil NO3-N (mg NO3-N kg soil-1)	Nitrate Level	Use N input	Soil P (mg P kg soil-1)	P Level	Use P input
Biv 347	Akiriamet	Benard Omusugu	6.78	Optimum	14.55	Very Low	Yes	0.50	Low	Yes

Soil K (mg K kg soil-1)	K Level	Use K input	Soil S (mg kg soil-1)	S Level	Use S input	Active C (mg kg soil-1)	C Level	Use organic input
20	Very Low	Yes	30.25	High	No	389.9	Low	Yes

Sample village comparison chart: Akiriamet village



Appendix A5: Sample tables

Table A5_1: Treatment 1 Balance Table

Variable	Treatment 1	Non-Treatment 1
Female	0.58 (0.49)	0.57 (0.49)
Age	47.75 (16.12)	48.48 (16.09)
Household size	5.52 (3.25)	5.39 (3.10)
Years education	7.76 (3.70)	8.02 (3.83)
Asset index†	0.01 (0.93)	0.03 (0.96)
TLU‡	1.21 (2.38)	1.07 (1.58)
Uses inorganic inputs	0.87 (0.34)	0.89 (0.31)
Uses organic inputs	0.42 (0.49)	0.47 (0.50)
Math ability	0.55 (0.50)	0.56 (0.50)
Widow	0.15 (0.36)	0.14 (0.34)
Usually home	0.98 (0.13)	0.98 (0.14)
NGO contact	0.11 (0.32)	0.14 (0.35)
Total acres	0.92 (0.85)	1.17 (1.13)***
Anglican	0.26 (0.44)	0.30 (0.46)
Catholic	0.19 (0.39)	0.16 (0.36)
Pentecostal	0.43 (0.50)	0.42 (0.49)
Other Christian	0.10 (0.30)	0.11 (0.31)
Other religion	0.02 (0.13)	0.02 (0.13)
Bukusu	0.35 (0.48)	0.38 (0.49)
Other Luhya	0.33 (0.47)	0.30 (0.46)
Iteso	0.29 (0.46)	0.29 (0.45)
Other tribe	0.03 (0.17)	0.03 (0.17)
Enumerator 1	0.23 (0.42)	0.20 (0.40)
Enumerator 2	0.30 (0.46)	0.29 (0.46)
Enumerator 3	0.23 (0.42)	0.30 (0.46)**
Enumerator 4	0.18 (0.39)	0.17 (0.38)
Enumerator 5	0.06 (0.24)	0.04 (0.18)

Standard deviations located next to respective means. † Asset index compiled through factor analysis after Sahn and Stifel (2003). ‡ Tropical Livestock Units. Difference between means T-test statistical significance: ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table A5_2: Treatment 2 Balance Table

Variable	Treatment 2	Non-Treatment 2
Female	0.54 (0.50)	0.59 (0.49)
Age	49.04 (15.82)	48.04 (16.19)
Household size	5.20 (3.64)	5.49 (2.96)
Years education	8.30 (3.64)	7.84 (3.84)
Asset index†	0.12 (0.98)	-0.01 (0.94)*
TLU	1.24 (1.74)	1.07 (1.85)
Inorganic inputs	0.90 (0.30)	0.88 (0.32)
Organic inputs	0.47 (0.50)	0.45 (0.50)
Math	0.59 (0.49)	0.55 (0.50)
Widow	0.15 (0.36)	0.14 (0.34)
Usually home	0.97 (0.16)	0.98 (0.13)
NGO contact	0.14 (0.35)	0.13 (0.34)
Total acres	1.15 (0.97)	1.09 (1.10)
Anglican	0.31 (0.46)	0.28 (0.45)
Catholic	0.17 (0.38)	0.16 (0.37)
Pentecostal	0.38 (0.49)	0.44 (0.50)
Other Christian	0.11 (0.31)	0.11 (0.31)
Other religion	0.03 (0.16)	0.01 (0.12)
Bukusu	0.34 (0.48)	0.38 (0.49)
Other Luhya	0.34 (0.48)	0.30 (0.46)
Iteso	0.29 (0.45)	0.29 (0.45)
Other tribe	0.02 (0.15)	0.03 (0.17)
Enumerator 1	0.23 (0.42)	0.20 (0.40)
Enumerator 2	0.29 (0.45)	0.30 (0.46)
Enumerator 3	0.29 (0.46)	0.27 (0.45)
Enumerator 4	0.16 (0.36)	0.18 (0.38)
Enumerator 5	0.03 (0.18)	0.05 (0.21)

† Asset index compiled through factor analysis after Sahn and Stifel (2003). ‡ Tropical Livestock Units. Difference between means T-test statistical significance: ***p<0.01, **p<0.05, *p<0.1.

Table A5_3: Treatment 3 Balance Table

Variable	Treatment 3	Non-Treatment 3
Female	0.62 (0.49)	0.57 (0.50)
Age	48.79 (16.32)	48.14 (16.03)
Household size	5.36 (2.37)	5.44 (3.34)
Years education	7.89 (4.08)	7.97 (3.71)
Asset index†	0.01 (0.96)	0.03 (0.95)
TLU‡	1.07 (1.55)	1.12 (1.90)
Inorganic inputs	0.90 (0.30)	0.88 (0.32)
Organic inputs	0.48 (0.50)	0.45 (0.50)
Math	0.55 (0.50)	0.56 (0.50)
Widow	0.14 (0.35)	0.14 (0.35)
Usually home	0.99 (0.12)	0.98 (0.14)
NGO contact	0.16 (0.36)	0.13 (0.34)
Total acres	1.07 (1.04)	1.12 (1.08)
Anglican	0.27 (0.45)	0.29 (0.46)
Catholic	0.16 (0.37)	0.17 (0.37)
Pentecostal	0.45 (0.50)	0.42 (0.49)
Other Christian	0.11 (0.31)	0.11 (0.31)
Other religion	0.01 (0.10)	0.02 (0.14)
Bukusu	0.39 (0.49)	0.37 (0.48)
Other Luhya	0.27 (0.44)	0.32 (0.47)
Iteso	0.31 (0.46)	0.28 (0.45)
Other tribe	0.03 (0.18)	0.03 (0.17)
Enumerator 1	0.18 (0.38)	0.22 (0.42)
Enumerator 2	0.30 (0.46)	0.29 (0.46)
Enumerator 3	0.31 (0.46)	0.27 (0.44)
Enumerator 4	0.18 (0.39)	0.17 (0.38)
Enumerator 5	0.03 (0.18)	0.04 (0.21)

† Asset index compiled through factor analysis after Sahn and Stifel (2003). ‡ Tropical Livestock Units. Difference between means T-test statistical significance: ***p<0.01, **p<0.05, *p<0.1.

Table A5_4: Control Balance Table

Variable	Control	Non-Control
Female	0.57 (0.50)	0.58 (0.49)
Age	47.67 (16.18)	48.50 (16.07)
Household size	5.60 (3.13)	5.36 (3.15)
Years education	7.88 (3.79)	7.98 (3.81)
Asset index†	-0.05 (0.94)	0.05 (0.96)
TLU‡	0.92 (1.44)	1.18 (1.94)*
Inorganic inputs	0.88 (0.33)	0.89 (0.31)
Organic inputs	0.46 (0.50)	0.46 (0.50)
Math	0.54 (0.50)	0.57 (0.50)
Widow	0.11 (0.32)	0.15 (0.36)
Usually home	0.98 (0.13)	0.98 (0.14)
NGO contact	0.14 (0.34)	0.14 (0.34)
Total acres	1.29 (1.32)	1.04 (0.96)***
Anglican	0.31 (0.46)	0.28 (0.45)
Catholic	0.14 (0.34)	0.18 (0.38)
Pentecostal	0.43 (0.50)	0.42 (0.49)
Other Christian	0.11 (0.31)	0.11 (0.31)
Other religion	0.01 (0.11)	0.02 (0.13)
Bukusu	0.41 (0.49)	0.36 (0.48)
Other Luhya	0.29 (0.46)	0.32 (0.47)
Iteso	0.27 (0.44)	0.30 (0.46)
Other tribe	0.03 (0.17)	0.03 (0.17)
Enumerator 1	0.21 (0.41)	0.21 (0.41)
Enumerator 2	0.29 (0.45)	0.30 (0.46)
Enumerator 3	0.29 (0.45)	0.27 (0.45)
Enumerator 4	0.18 (0.38)	0.17 (0.38)
Enumerator 5	0.04 (0.20)	0.04 (0.20)

† Asset index compiled through factor analysis after Sahn and Stifel (2003). ‡ Tropical Livestock Units. Difference between means T-test statistical significance: ***p<0.01, **p<0.05, *p<0.1.

Table A5_5: Average Bids by Treatment and Auction Round

Input	Treatment 1		Treatment 2		Treatment 3		Control	
Baseline Auction	**Mean (Std)**	**N**	**Mean (Std)**	**N**	**Mean (Std)**	**N**	**Mean (Std)**	**N**
DAP (1kg)	87.49 (41.36)	233	85.64 (33.62)	218	80.29 (33.59)	205	80.83 (29.84)	228
DAP (5kg)	359.13 (151.40)	229	382.39 (166.37)	211	366.41 (162.38)	202	367.30 (154.82)	226
Biochar (1kg)	70.26 (45.30)	233	69.52 (40.54)	218	63.05 (35.03)	205	65.70 (37.32)	228
Biochar (5kg)	270.79 (143.72)	228	277.66 (148.36)	214	280.37 (145.11)	203	272.71 (147.28)	225
Compost† (1kg)	82.92 (49.70)	233	89.29 (48.85)	218	75.18 (37.92)	205	80.92 (45.79)	228
Compost (5kg)	307.85 (152.38)	223	337.10 (170.33)	207	325.05 (166.04)	199	327.58 (161.42)	225
Biochar/DAP Mix (1kg)	77.66 (46.45)	233	84.29 (54.87)	218	75.81 (48.33)	205	73.62 (38.14)	228
Biochar/DAP Mix (5kg)	288.87 (148.59)	226	302.24 (146.44)	208	301.93 (150.96)	200	291.10 (144.63)	223
Biochar/Compost Mix (1kg)	69.21 (43.71)	233	70.07 (40.19)	218	66.71 (36.74)	205	67.15 (35.23)	228
Biochar/Compost Mix (5kg)	278.69 (139.11)	226	295.71 (158.56)	211	289.95 (162.67)	197	287.85 (144.53)	223
Cow Manure (5kg)	125.04 (115.90)	228	121.51 (121.88)	213	116.63 (117.66)	204	121.81 (112.58)	225
Cow Manure (25kg)	335.84 (247.06)	215	322.58 (257.92)	200	291.12 (228.87)	183	343.69 (253.45)	213
Second Auction	**Mean (Std)**	**N**	**Mean (Std)**	**N**	**Mean (Std)**	**N**	**Mean (Std)**	**N**
DAP (1kg)	82.25 (39.78)	233	85.90 (35.61)	218	80.20 (39.64)	205	80.88 (37.92)	228
DAP (5kg)	345.02 (160.46)	229	383.15 (167.50)	211	358.12 (167.99)	202	359.67 (155.56)	226
Biochar (1kg)	67.62 (42.57)	233	67.13 (35.83)	218	63.02 (33.85)	205	67.83 (37.20)	228
Biochar (5kg)	269.47 (127.85)	228	281.31 (156.63)	214	279.16 (138.15)	203	276.87 (141.41)	225
Compost† (1kg)	81.29 (43.78)	233	86.01 (46.81)	218	76.56 (42.32)	205	80.90 (39.45)	228
Compost (5kg)	307.67 (143.38)	223	329.88 (166.83)	207	310.81 (155.09)	199	321.38 (158.08)	225
Biochar/DAP Mix (1kg)	78.78 (44.99)	233	81.12 (45.26)	218	75.31 (43.72)	205	76.56 (39.47)	228
Biochar/DAP Mix (5kg)	293.81 (135.58)	226	308.72 (144.50)	208	304.08 (142.88)	200	296.26 (147.37)	223
Biochar/Compost Mix (1kg)	74.00 (45.37)	233	75.14 (40.85)	218	71.54 (49.61)	205	67.92 (33.89)	228
Biochar/Compost Mix (5kg)	285.88 (143.68)	226	296.78 (154.31)	211	288.83 (143.77)	197	278.43 (130.52)	223
Cow Manure (5kg)	128.97 (116.74)	228	127.50 (126.53)	213	130.72 (144.63)	204	120.71 (111.98)	225
Cow Manure (25kg)	340.18 (244.63)	215	332.59 (257.99)	201	294.27 (242.12)	184	329.58 (250.94)	213

Uneven N sizes due to the trimming of the sample (as discussed in text). † The compost that was auctioned was vermicompost, produced by Dudutech company in Kenya.

Appendix A6: Between group variances

Table A6_1: P-values for Differences between Group Variances

Overall				
Treatment	IR	VC	IR&VC	Control
IR	.	0.045	0.816	0.000
VC	0.045	.	0.092	0.000
IR&VC	0.816	0.092	.	0.000
Control	0.000	0.000	0.000	.
Men				
Treatment	IR	VC	IR&VC	Control
IR	.	0.000	0.873	0.000
VC	0.000	.	0.002	0.000
IR&VC	0.873	0.002	.	0.000
Control	0.000	0.000	0.000	.
Women				
Treatment	IR	VC	IR&VC	Control
IR	.	0.945	0.816	0.000
VC	0.945	.	0.877	0.000
IR&VC	0.816	0.877	.	0.000
Control	0.000	0.000	0.000	.

Means and Standard Deviations for each group are in Table 4. P-values result from test statistics after Levene (1960) and are robust to the underlying distribution of the data.

Appendix A7: Parallel paths assumption

Identification based on difference-in-differences regressions relies on the assumption that the two groups being compared would have the same general trajectory over time in the absence of an intervention. We believe that because the treatment and control groups were randomly assigned at the auction and the groups are generally well-balanced, we can assume that the parallel path trend applies to these groups. Here, we analyze whether we can make the same assumption for those who received different information. For example, in treatment 1, we need to demonstrate that in the absence of information, those who received recommendations to use organic inputs would have on average changed their bids in the same manner as those who did not receive a recommendation to use these inputs. Because the recommendations are based on the soil nutrient levels of an individual's farm, it is possible (though seemingly unlikely), that they may behave in a fundamentally different way based on their own soil characteristics. We can easily test for this by looking at the control group, which did not receive any information treatment. However, we have information about what the recommendation would have been for each individual if they were in the treatment group. We can thus compare the differences between these two groups among those who did not receive a treatment.

In columns I and III of Table A7_1 we show results of a difference-in-differences estimation among those in the control group, looking at the difference between whether they would have received the input recommendation if they had been randomly assigned to the treatment group. As expected, for both the nitrogen and organic recommendation, there are no statistically significant differences between the change in bids between the first and second auctions. Similarly, in Table A7_2, we do the same estimation but divide the control group by whether they would have seen their position on the village soil charts as above or below that of their peers. Columns I and III in Table A7_2 also show no significant differences. This leads us to conclude that the parallel path assumption holds for the triple difference estimation.

When we include gender however, we need to show parallel paths for men and women. We look at this difference among those in the control group conditional on whether they would have received the input recommendation for treatment 1 or seen they had above average soil quality in treatment 2. These results are in Columns II and IV in Tables A7_1 and A7_2, and we find no significant differences between men and women. These results suggest that conditional on the potential information treatment, there are parallel paths between men and women.

Table A7_1: Difference-in-Differences Results: Parallel Path Checks

		DAP		Organic inputs	
		I	II	III	IV
Use N × time	Treatment effect	-8.880	2.318		
	SE	6.078	5.386		
	Cluster p-value	0.163	0.673		
Use N × time × female	Treatment effect		-19.681		
	SE		13.109		
	Cluster p-value		0.153		
Use O × time	Treatment effect			-0.944	5.558
	SE			4.840	5.645
	Cluster p-value			0.848	0.339
Use O × time × female	Treatment effect				-12.457
	SE				8.874
	Cluster p-value				0.179
Covariates		Yes	Yes	Yes	Yes
F.E. (Village, enumerator, month, input, input × time)		Yes	Yes	Yes	Yes
N		900	900	4452	4452
R^2		0.520	0.520	0.675	0.677

Standard errors (SE) are clustered at the village level. ***p<0.01, **p<0.05, *p<0.1.

Table A7_2: Difference-in-Differences Results: Parallel Path Checks

		DAP		Organic inputs	
		I	II	III	IV
Avg Quintile>3 × time	Treatment effect	-2.776	-10.548	3.476	7.631
	SE	5.087	6.453	3.691	4.672
	Cluster p-value	0.593	0.122	0.360	0.122
Avg Quintile>3 × time × female	Treatment effect		13.779		-7.340
	SE		12.354		5.171
	Cluster p-value		0.281		0.175
Covariates		Yes	Yes	Yes	Yes
F.E. (Village, enumerator, month, input, input × time)		Yes	Yes	Yes	Yes
N		900	900	4452	4452
R^2		0.518	0.519	0.675	0.680

Standard errors (SE) are clustered at the village level. ***p<0.01, **p<0.05, *p<0.1.