Private Contributions for Public Information: Soil Testing in Malawi

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Abstract

We implement a public goods experiment in Central Malawi that asks small-scale farmers to contribute to the cost of a soil test, the results of which provide public information with private value. By randomly varying the plot selected for soil testing within each village, we examine the role of soil heterogeneity and free-riding in determining contributions. Farmers contribute a considerable amount to the soil test and increase their contribution if they perceive the plot selected to be similar to their own. Higher village-level soil heterogeneity is associated with reduced free-riding, increasing the likelihood of a fair equilibrium in which farmers provide similar contributions.

Keywords: public goods, framed field experiment, information provision, soil fertility test, value of agricultural information, Malawi

JEL Classification: H41, O13, O33, Q16, Q51

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1 Introduction

Information provided to a single individual can also have value to others; once provided, it is difficult to exclude others from accessing it. This "public goods" nature of information has important implications for its provision as well as for information sharing and learning.

The voluntary provision of information (and all other public goods) is, however, characterized by free-riding (Bergstrom, Blume and Varian, 1986) so that investment in the generation of knowledge can be delayed as individuals wait on others to invest. In agriculture, this implies that experimentation by farmers can exhibit strategic delays (as Foster and Rosenzweig (1995) show was the case in India's Green Revolution). In effect, this is why provision of new agricultural technologies is traditionally the domain of governments, and why public agricultural extension services play a critical role in introducing new agricultural information and practices (Anderson and Feder, 2007; Aker, 2011). Local governments, however, often lack necessary resources to deliver agricultural information to rural populations. We examine a possible alternative provision mechanism – collective contributions to provide a local public good.

We focus on soil testing with small-scale farmers in Central Malawi, a region with limited access to agricultural extension services, government or otherwise. A soil test provides information about current soil fertility status as well as management recommendations to remedy limiting nutrient deficiencies, thus offering actionable information to raise agricultural yields and revenues (Harou et al., 2020; Corral et al., 2020; Tamim et al., 2020). Depending on the extent of spatial variation in soil characteristics, there may be strong positive externalities to the provision of a single soil test in a village and the degree to which the information is a public good.[1] The success of providing information through private contributions, however, depends on the degree of free-riding among farmers.

We played four rounds of a modified public goods game in 30 randomly chosen villages to provide insight into farmers' valuation of soil information in a setting where the public goods aspect of information was made explicit. Our framed field experiment incorporated the naturally-occurring environment with respect to the public good, stakes, and participant information sets. We provided 20 farmers in each village with 2,000 Malawian Kwacha (MK) (about 3 $US at the time of the experiment) and asked them to contribute towards a series of soil tests with accompanying management recommendations: each round of the experiment was in reference to a different village plot randomly chosen from the set of the plots constituted by the participant farmers. Both the cost of the soil test (7,000 MK or about 10 $US) and the location of the plot selected for a soil test in each round were known

[1]In the limit, high spatial correlation in soil characteristics would mean that a single soil test and associated management recommendations would be relevant to all of a country's farmers.

by the farmers. Contributions, however, were recorded in private. Only one of the plots (one of the four rounds) was randomly selected for implementation and testing if the total village contributions in that round exceeded the soil test cost.

We performed the soil analysis in the villages once the experimental rounds ended: a trained field technician collected a composite soil sample from the selected plot and analyzed it for soil texture, pH, and electrical conductivity (EC) in the back of a pick-up truck using SoilDoc (Weil and Gatere, 2015), a portable wet-chemistry-based lab designed for in-the-field soil analysis. An agronomist then provided villagers with an initial assessment of soil fertility and management recommendations, with more detailed recommendations based on a complete set of soil analysis results delivered at a later date.

Our design has two advantages. First, the random selection of plots to be sampled generated experimental variation in valuation among the participants across the various game rounds. Second, the random selection of villages provided variation in village-level soil heterogeneity, as well as village-level social connectivity.[2]

We find that farmers contribute a considerable amount towards the soil test, suggesting that they both expect to learn from each other's soil tests, and are willing to pay for such information. Average individual contributions are 45% of the endowment – around 900 MK – implying an average total village contribution of 18,000 MK, significantly exceeding the 7,000 MK cost of the soil test. Individual contributions vary depending on farmers' perceptions of soil similarity between the chosen plot and their own. Exploiting variation across rounds, we find that farmers contribute 2.2 to 4.5 percentage points more (compared to an average of 45%) when they perceive that the sampled soil is similar to their own. Farmers also contribute more towards soil test from plots of their family and friends.

To understand what farmers mean by similarity across plots it is important to note that farmers distinguish between the observable soil characteristics like color and texture and the unobserved agronomic fertility of soils (Berazneva et al., 2018; Maertens, Michelson and Nourani, 2021). When a farmer states a soil is similar, she generally makes a reference to the observable features. In this paper, we refer to observable characteristics as soil types. However, despite their knowledge of types, farmers are often unsure about how to improve soil fertility, which is not directly observed or proxied by the observed characteristics. Soil tests provide information about this unobservable component.

We develop a theoretical model framing these dimensions of soil characteristics, valuation, and equilibrium responses. In our model, each farmer is endowed with a plot of a specific soil type, known by the farmer and by the other farmers in the village. For each soil type,

[2]While the latter is not a main focus of this paper, we acknowledge the possibility that farmers may contribute more to soil tests which benefit their relatives or friends.

an optimal level of fertilizers maximizes the yield for that type (i.e., soil type and fertilizer jointly determine agricultural yields). The optimal level of fertilizers is, however, not known with certainty by any farmer, and is exactly what our soil test provides information about. In the experiment, the farmers contribute to this discrete public good. In essence, each farmer decides on her contribution for the soil test, knowing that other farmers do so as well. We show that, within each soil type, there are three types of equilibria: (1) the zero-contribution equilibrium in which no soil test is provided, (2) the equal-contribution equilibrium in which each farmer contributes the same share of their valuation (a "fair" equilibrium), and (3) an infinite number of unequal-contribution equilibria in which farmers contribute different shares of their valuation, and hence free-riding is dominant. Overall, we expect the distribution of soil types in the village, i.e., soil heterogeneity, to affect the pattern of contributions we observe.

Exploiting the natural variation in soil heterogeneity between the villages, we take this insight to the data. We find that an increase in soil heterogeneity in the village is associated with an increase in the average level of farmer contributions and a decrease in the dispersion of contributions (measured through the coefficient of variation). This is indicative of a move towards a fair equilibrium, rather than an equilibrium in which free-riding dominates. When we simply consider the relationship between the number of farmers within each soil type contributing towards a soil test of a plot of their type, we also see an increased dispersion in contributions as the number of farmers increases. Both results suggest that when village soil heterogeneity increases, there is a lower scope for free-riding as the soil test loses its "public goods" nature.

We make two primary contributions to the literature. First, we contribute to the literature on effective delivery of information to farmers in low-income countries (see, for example, empirical work of Fabregas, Kremer and Schilbach (2019); Casaburi et al. (2019); Rosenzweig and Udry (2019) and reviews in Nakasone, Torero and Minten (2014) and Aker, Ghosh and Burrell (2016)). Our focus on providing information through collective contributions distinguishes our study from previous research that has tended to focus on private delivery of information. Closest to our work, Fabregas et al. (2017) elicited Kenyan farmers' willingness-to-pay (WTP) for a soil test from a nearby plot and found WTP between 2 and 5 $US per soil test, significantly below the 10 $US marginal cost of a test in their study. We show, in contrast, that the *aggregate* private contributions to a similarly-priced single soil test exceed the marginal cost of the soil test provision. This alternative mechanism for delivery of agricultural information suggests a new, cost-effective design for some aspects of public extension or may be plausible at scale (Fabregas, Kremer and Schilbach, 2019).

While our work is agnostic regarding whether and how much farmers should value agricultural information – a soil test in our context – a handful of recent studies have focused on the effects of soil testing on farmer investment. Their results suggest private benefits to local information but show that farmers face financial constraints, which can prevent them from acting on this information. For example, Murphy et al. (2020) used experimental auctions in Kenya to show that soil information increased farmers' willingness-to-pay for agricultural inputs. Harou et al. (2020) found that management recommendations based on plot-level soil tests increased fertilizer use and maize yields in Tanzania but only when combined with subsidies to purchase the inputs. Corral et al. (2020) found that plot and cluster-level recommendations both had modest effects on farmer adoption of improved agricultural practices in Mexico. Our study offers an alternative and experimentally-elicited valuation of local agricultural information. Farmers universally reported that a soil test would be useful, contributed a significant amount towards the soil test, and increased their contributions towards plots with (perceived) similar soils.

Second and more generally, our results contribute to an extensive literature on the provision of public goods in the field.[3] We focus on private provision of public information that could lead to improvements in the productivity of important private assets (agricultural land, yields, and profits). Private contributions for the construction and maintenance of local public goods such as roads, schools, bridges, and water systems are common in developing countries (Ostrom, 1990; Olken and Singhal, 2011). Framed public goods experiments have been used to examine their delivery, but also to understand the role of, for example, social learning (Turiansky, 2017) or risk (Cardenas et al., 2017). Our work is among a small number of studies using threshold public good games conducted in the field in which the public good is actually provided. Saldarriaga-Isaza, Villegas-Palacio and Arango (2015) examine private contributions towards a purchase of technology to recover gold in Colombia; and Carlsson, Johansson-Stenman and Khanh Nam (2015) study contributions towards building a bridge in Vietnam. Similar to these two studies, we demonstrate that private provision of a local public good is possible but also allow for heterogeneous valuation of a public good and shed light on the degree and reasons behind free-riding in determining individual contributions.

The rest of the paper is structured as follows. In the next section, we provide information on the Central Malawi setting and explain the potential value of providing soil testing. Section 3 introduces our sample, experiment, and data collected, while Section 4 presents descriptive analysis. We discuss our individual-level estimation in Section 5. In Section 6 we develop a theoretical model to understand the role of soil heterogeneity and free-riding, and

[3] Analyses of public good games conducted in laboratory and field settings have generally found that participants to public goods games do not free-ride as much as theoretically predicted, though free-riding usually increases over time in multi-period games (Ledyard, 1995; Chaudhuri, 2011; Vesterlund, 2017; Henrich, 2004; Nourani, Maertens and Michelson, 2021). Our findings are in line with this literature.

we empirically test the model's prediction in Section 7. Finally, Section 8 draws conclusions for research and policy.

2 Background

While cereal yields in South America and Asia have doubled since the 1960s and now average 4-5 metric tons per hectare, cereal yields in Sub-Saharan Africa lag far behind, averaging 1.5 metric tons per hectare (FAO, 2019*a*). In Malawi, maize grain yields on smallholder farms are 2 tons per hectare and yields of the primary cash crops tobacco and soybean are also low – each averaged a little more than one ton per hectare in 2018 (FAO, 2019*a*).[4] Low crop yields in Malawi, as elsewhere in Sub-Saharan Africa, have been attributed to low soil fertility, population pressure, increasingly erratic rainfall, low uptake of improved agricultural technologies, limited access to extension services and incomplete or imperfect credit, input and output markets (see, for example, Marenya and Barrett (2009), Mhango, Snapp and Phiri (2013), Snapp et al. (2014), Burke, Snapp and Jayne (2020)).

Among these, issues related to low soil fertility have received considerable attention of late among both researchers and policy-makers; soil fertility is both low and declining in much of Sub-Saharan Africa (Njoloma et al., 2016; Tully et al., 2015; Sanchez, 2002). Central Malawi's soils are classified as Ferralsols, Lixisols, and Plinthosols (FAO, 2019*b*).[5] A common feature of these soils is that the addition of organic and inorganic fertilizer can improve their structure and overall fertility. However, despite Malawi's recent fertilizer subsidy program, farmers in 2016 only applied 18 kilograms of fertilizer per hectare of maize, far below recommended rates for the region (FAO, 2019*a*).

One possible explanation for low fertilizer use is that the benefits to fertilizer use are heterogeneous, conditional on initial soil fertility and structure (Place et al., 2003; Vanlauwe and Giller, 2006; Marenya and Barrett, 2009; Mugwe et al., 2009; Suri, 2011; Hurley, Koo and Tesfaye, 2018). This heterogeneity in the benefits to fertilizer application may relate both to the amount and to the type of fertilizer applied. While soil fertility is, on average, low in most of Malawi, evidence suggests important spatial variability in the primary nutrient constraints. Figure A1 in the appendix summarizes the results of 2,700 soil tests recently conducted in Central Malawi. All soils are deficient in nitrogen (N) – a key element for plant growth, however, further deficiencies are split across one or more macro nutrients:

[4]In contrast, the average yields of Southern America and Asia are, respectively, 5.8 and 5.4 tons per hectare for maize; 3.0 and 1.9 tons per hectare for tobacco; and 2.3 and 1.4 tons per hectare for soybean (FAO, 2019*a*).

[5]The former are old, weathered soils, sandy-loam free-draining with resulted low nutrient content and possibly acid pH. Lixisols are more sandy-textured version of Ferralsols and hence more subject to erosion. Plinthosols typically have a hardened layer of iron and/or aluminium deposits impeding water flow and root development.

phosphorus (P), potassium (K), and sulfur (S). The variation implies that the type and rate of fertilizer applied are of consequence. For instance, urea only addresses a nitrogen deficiency, while NPK addresses deficits in nitrogen, phosphorus, and potassium.

Despite evidence of important variation in soil nutrients, fertilizer recommendations in many Sub-Saharan African countries are still made at the national or regional level. In order for farmers to make informed decisions as to which fertilizer, and how much, to apply, however, they may require more locally calibrated information about the particular nutrient deficiencies in their soils.

At the same time, soil testing remains rare outside of large commercial farms and experimental plots in Malawi and in the Southern African region more generally, both due to limited number of laboratories and costs of soils testing. We are unaware of any agricultural extension services – whether through the government or non-governmental organizations – providing low-cost soil testing to farmers in Malawi.

Finally, even if such soil testing was widely available, research suggests that small-scale farmers' willingness to pay (WTP) for soil information is relatively low and unlikely to cover the cost of provision. Fabregas et al. (2017), for example, elicited Kenyan farmers' WTP for a soil test from a nearby plot to find the WTP in the 2-5 $US range per soil test, significantly below the test's marginal cost of 10 $US.

3 Sample, experiment, and data collected

We implemented our experiment in collaboration with 30 villages in Central Malawi in June and July of 2019. In each village, we conducted four rounds of a modified public goods game, collected demographic data, and took soil samples.[6] Below we describe the participant sample, data collected, and discuss the experimental design and soil sampling procedures. The protocols used are included in the appendix.

3.1 Sample and experiment

Our work builds on a prior impact evaluation study, a randomized controlled trial to examine the impacts of an agricultural extension program on farmers' adoption of yield-enhancing integrated soil fertility management (ISFM) practices that was carried out in Central Malawi from 2014 to 2019 (Maertens, Michelson and Nourani, 2021).[7] While this

[6]Our team included one agricultural economist, a soil scientist, an agronomist, and an agricultural extension specialist, in addition to the authors.

[7]The ISFM impact evaluation was conducted in two Extension Planning Areas (EPAs) – Chibvala and Mtunthama (EPA is a sub-district administrative unit). It included 300 out of the 303 villages which counted at least 50 households according to the 2014 village census of the District Agricultural Offices. In this study, we randomly selected 30 villages, stratified by EPA from the 150 control villages of the ISFM impact evaluation. Our final sample for this study includes 15 villages in Chibvala EPA (Dowa district) and 15 villages in Mtunthama EPA (Kasungu district).

prior ISFM impact evaluation is not the focus of this paper, working in the area of our prior study affords two primary advantages. First, we can use our larger representative data set for the area to establish the external validity of our smaller sample. Second, we have established a relationship of trust with the farmers, which was important as we asked them to contribute towards something they would not receive right away in its entirety.[8]

We limited the sample to 20 farmers in each village for the public goods experiment; invitees were randomly selected from a census list obtained from the District Agricultural Offices. We worked with village elders to reach the desired number of 20 farmers per village to achieve approximately equal representation of female and male farmers, with individuals invited ahead of time from a randomly-ordered list of households, with several replacement options. Village visits within a single district were planned accordingly to minimize communication and spillovers between villages. The final sample consists of 600 individuals, almost equally split between female and male farmers.

Participants played a modified threshold public goods game with continuous contributions, money-back guarantee, and proportionate rebate rule. Public goods games have been commonly used in developing-country settings to measure cooperative behavior (see, for instance, Visser and Burns (2015), Tsusaka et al. (2015), and Henrich (2004) for an overview).

From their endowment of 2,000 Malawian Kwacha (MK) (approximately 3 $US, the median daily cash income), we asked the participants to privately contribute towards one soil test accompanied by management recommendations, which would be shared with all participants.[9] The price of the soil test was set at 7,000 MK (10 $US), its marginal cost. Only if collective contributions were the same or exceeded this cost of the soil test, we did the soil test in that village, with residual contributions returned to farmers in a manner proportionate to the individuals' contributions.[10] Carlsson, Johansson-Stenman and Khanh Nam (2015), for instance, ask villagers in Vietnam to contribute to the construction of a public good, a bridge, using a similar set-up as ours.[11]

[8]Trust has been shown to be an important factor when farmers engage with others (see, among others, Buck and Alwang (2011) and Fischer and Wollni (2018)). In order to further address trust issues we also conducted a component of the soil testing on site, in the village.

[9]Our focus is on a soil test from one plot only, i.e. we opted for a discrete decision framework (as opposed to allowing farmers to contribute to multiple soil tests). While a continuous decision framework is of interest from a policy perspective, i.e., how many plots need to be tested from the farmers' view, it would not allow us to reveal the plots characteristics pre contribution, and hence would not allow us to study the bilateral relationship between plots' and farmers' characteristics in the data.

[10]The exact nature of the rebate rule can affect the overall contributions (see, among others, Marks and Croson (1998), Cadsby and Maynes (1999), Spencer et al. (2009)). The use of a proportional rebate is common when dealing with discrete public goods. While there are other ways to run a discrete public goods game, we took inspiration from a laboratory experimental literature on discrete public goods, and concluded that a proportional rebate was more likely to generate at least some contributions in our setting.

[11]Prior to our study, we had carefully field-tested the experiment in four non-sample villages. During this

The experiment proceeded as follows (Figure A.2 in the appendix provides an overview of the timeline). In each village, the selected participants gathered in a central location, secluded from the rest of the village to avoid bystanders. Following welcome remarks and introductions by the agricultural extension specialist, we explained the purpose of our visit. The agronomist spoke about the importance of knowing one's soil, as well as the possible short- and long-term soil health and yield benefits of adopting tailored fertilizers and other soil management techniques. We introduced the soil scientist, equipped with a mobile soil laboratory, to instill confidence in the participants.

We then recorded the participants' names and numerical identifiers (using randomly-drawn bingo balls to assign them) and asked the participants to mark their maize plot on a large color map of the village (printed from Google Earth). For participants with more than one plot, we asked to indicate the maize plot with the highest agricultural value to them. Once the participants indicated the location of their plots, we asked the group to discuss and indicate the village soil types on the map (an example of a map with marked maize plots and soil types is shown in Figure 1).

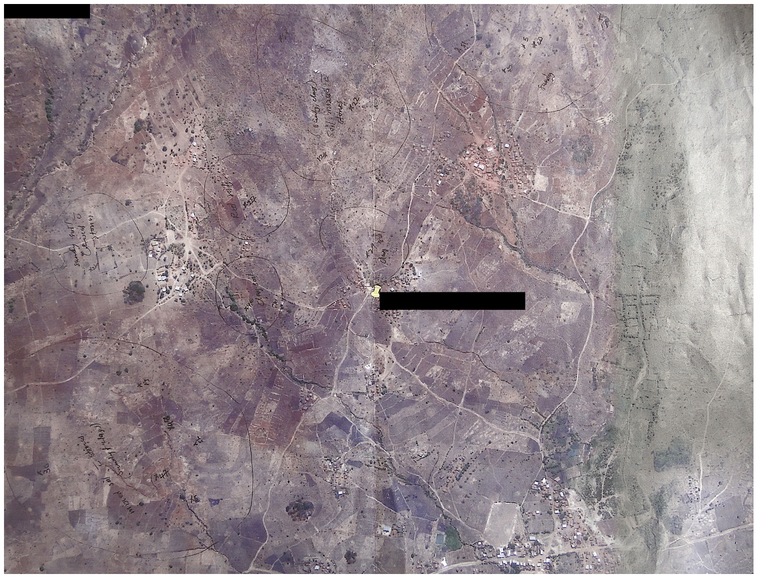
The economist on the team then explained our experiment. Each participant was to play four rounds of our game and, in each round, decide, in private, how much of the endowment to contribute towards the soil testing of a selected plot and how much to keep for themselves. We emphasized the fact that the decision would be confidential, and only the researcher would know how much each participant was contributing. For each of the first three rounds, we randomly chose a plot for soil test by drawing a numbered bingo ball.[12] For the final, fourth round, we asked the participants to gather around the village map and collectively decide on the plot for soil test (among the plots of the participating farmers). We told the participants that while they should imagine starting each round with the 2,000 MK endowment, only one round would be chosen for actual payout and soil test.

We then proceeded with the four rounds of the experiment. During the experiment, substantial care was taken to avoid communication between the participants – participants

field testing, we varied the number of participants, the endowment and cost of the soil test, the method of selecting the plot to be tested, the number of plots to be tested, and the sequencing of the experiment. We are confident that our resulting experiment not only was well understood by the participants, but that the method of randomly drawing a plot to be tested resulted in meaningful estimates and insights. We refined the survey questions which accompanied the experiment to ensure they were well understood. We also note that the literacy levels and education levels were reasonably high among our participants: Table 1 shows that, on average, farmers in our sample completed 6 years of education. Table A.1 in the appendix presents the data from the 250 villages of the ISFM impact evaluation (from which these 30 villages are a sub-sample). In these villages we had conducted a numeracy test, and noted that 96% of the household heads could count up to 20, and up to 50% of household heads noted numerical information to be useful, in general.

[12]In order to contribute to the perception of randomness, we allowed a young child to draw the balls from a cotton bag with bingo balls with identifiers for all participating farmers.

Figure 1: Example of a soil map used in the study.



Notes: The map shows one of the study villages, marked with soil types and the locations of farmers' plots. Soil types indicated include sandy, clay/red, sandy and stone, and sandy, clay, and stone.

were seated away from each other and asked not to talk to each other until the team recorded individual contributions for all four rounds. We played the rounds sequentially, i.e., a bingo ball was drawn with the plot identifier, and one by one, participants met with researchers located at various corners of the location where the experiment took place, recording the contributions for that round. Only when all contributions were recorded, we would continue with the next round. This process avoided recall error, as the participant would have each plot in mind when offering their contribution.[13]

After the contributions in all rounds were recorded, we selected a random round, again by using the cotton bag of bingo balls. It was only at that stage that we revealed whether the collective contributions exceeded the set cost of the soil test. By doing so, we avoided potential order effects caused by learning about other participants' behavior (as widely documented, in, for example, Chaudhuri (2011)). When the collective contributions exceeded the cost of the soil test for the selected round (which they almost always did), farmers were invited to follow the soil scientist to the plot to sample the soil.

3.2 Data collected

When recording the contributions after each round, we also asked participants how similar was the soil of the chosen plot compared to the respondent's indicated plot, and the

[13]During the actual (not-pilot) experiment, only the local, Malawian researchers were present in order to avoid the potential, so-called white men effect of Cilliers, Dube and Siddiqi (2015).

relationship with the owner of the chosen plot.[14]

While waiting for the soil analysis results, we conducted a short survey among all participants. We recorded their gender, age, marital status, education, the acreage of land owned and rented in, and (perceived) characteristics of their primary maize plot. We also asked farmers how useful it would be for them to receive soil fertility test for their indicated plot and collected some additional village-level information from village elders. We then calculated and distributed final payouts (individual payout = initial endowment − contribution in the chosen round + proportional rebate).

3.3 Soil tests

We tested onsite for soil texture, pH, and electrical conductivity (EC) using a portable SoilDoc kit (Gatere, 2013; Weil and Gatere, 2015). Based on these characteristics, the soil scientist and agronomist gave the participants, as a group, our initial soil status report and preliminary management recommendations that included both specific fertilizer blends, lime if pH was low, and organic inputs.

We took the soil samples to the Bunda College Soil and Plant Analysis Laboratory for further analysis where we tested the soil for nitrate nitrogen (NO_3^-), inorganic phosphorus (P), sulfur (S), exchangeable potassium (K), and active soil carbon (C).[15] When returning to the villages to share the final soil test results and management recommendations (an example is shown in the appendix), we collected four additional soil samples – three soil samples from the other three plots chosen in each of the remaining three rounds, plus one randomly sampled plot from the list of farmers who participated in the experiment. In total, we collected and tested five soil samples per village.

4 Descriptive analysis

Table 1 (panel A) introduces the experiment participants.[16] Individuals in our study area are predominantly involved in farming, trading, and agriculture-related businesses. Almost all own land (2.64 acres on average), some also rent land (0.33 acres, on average, in the last agricultural season). All participants grow maize – the primary crop in much of East and Southern Africa. About 80% of the sample is in a monogamous marriage and 4% of the sample is in a polygamous marriage; the rest of the participants are either widowed,

[14] The exact questions were: "How similar is this plot's soil to yours?" (1 = almost the same, 2 = somewhat similar, 3 = not at all similar, 4 = don't know or no opinion) and "What is your relation with this plot's owner?" (1 = my parent/child, 2 = other family, 3 = friend, 4 = just other villager).

[15] Active carbon is more sensitive to management effects than total organic carbon, and more closely related to soil productivity and biologically mediated soil properties, such as respiration, microbial biomass, and aggregation (Weil et al. (2003)).

[16] In Table A.2 in the appendix we aggregates these demographic statistics at a village-round level and compute the mean and standard deviation, or percentage for each variable at this level.

Table 1: Individual-level summary statistics.

Variables	N (1)	Mean (2)	St.dev. (3)	Min (4)	Max (5)
Panel A: Demographics					
Respondent is female (=1)	600	0.488	0.500	0	1
Respondent's age	600	39.76	14.44	17	88
Education (years completed)	600	5.885	3.744	0	16
Monogamous married (=1)	600	0.802	0.399	0	1
Polygamous married (=1)	600	0.0383	0.192	0	1
Widowed (=1)	600	0.0650	0.247	0	1
Separated/divorced (=1)	600	0.0667	0.250	0	1
Not married (=1)	600	0.0283	0.166	0	1
Land owned by household (acres)	600	2.644	2.806	0	32.50
Land rented in last season (acres)	600	0.334	0.962	0	17
Panel B: Soil fertility perceptions					
Plot's soil is very poor (=1)	600	25.67			
Plot's soil is somewhat poor (=1)	600	36.33			
Plot's soil is average (=1)	600	31.33			
Plot's soil is somewhat good (=1)	600	5.83			
Plot's soil is very good (=1)	600	0.83			
Soil erosion on primary maize plot (=1)	600	0.633	0.482	0	1
Nutrient depletion on primary maize plot (=1)	600	0.652	0.477	0	1
Water logging on primary maize plot (=1)	600	0.297	0.457	0	1
Useful to have a soil test (=1)	600	0.965	0.184	0	1
Panel C: Rounds 1-3 (random)					
Contribution to soil test as percentage of 2000 MK	1,710	44.96***	33.51	0	100
Same soil type from map (=1)	1,710	0.484	0.500	0	1
Similar soil from survey (=1)	1,710	0.453***	0.498	0	1
Distance to plot selected (km)	1,671	0.643	0.421	0	2.015
Belongs to family/friend (=1)	1,710	0.303	0.460	0	1
Panel D: Round 4 (chosen)					
Contribution to soil test as percentage of 2000 MK	570	51.76***	35.80	0	100
Same soil type from map (=1)	570	0.456	0.499	0	1
Similar soil from survey (=1)	570	0.358***	0.480	0	1
Distance to plot selected (km)	563	0.667	0.451	0	1.944
Belongs to family/friend (=1)	570	0.286	0.452	0	1
Panel E: Contributions to soil test from own plot					
Contribution to soil test as percentage of 2000 MK	120	45.63	32.88	5	100

Notes: Panel A shows demographic characteristics for all farmers in the sample (30 farmers in each of the 20 villages), while panel B presents farmers' perceptions about the soil fertility of their primary maize plot. Panels C and D show summary statistics for the dependent and independent variables in the random rounds and the fourth round, respectively. Here, observations for farmers' own plots are excluded. ***Means reported in panels C and D are statistically different at 1% for contribution to soil test and same soil type from survey.

separated, or not ever married. On average, respondents have six years of education, however, there is considerable variability in educational attainment across the respondents.[17]

4.1 Soil characteristics

We distinguish between two dimensions of soil characteristics. The first dimension, which we will refer to as "soil type," captures visually-observed physical characteristics of the soils – texture and color. The second dimension, which we will refer to as "soil fertility," reflects the nutrient content, which corresponds to the unobserved, soil chemical properties, and depends on local geology and climate, but also on cropping history and management practices. The relationship between observed soil type and unobserved soil fertility is sufficiently complex that the details of the nutrient content can be considered unknown to the farmer.[18]

Our experiment provides information about soil fertility to farmers. We used lab-based measures to assess the properties of local soils and quantify soil nutrient limitations. Using these, we provided detailed information about soil fertility and associated management recommendations including guidance on optimal types and quantities of agricultural inputs for increasing maize yields and for building long-term soil fertility.[19]

4.1.1 Soil types

We obtained information on soil types from the farmers. At the start of the experiment, farmers used a village map to describe soil types and identify regions of soil types within the village. On average, farmers identified three soil types per village (with a minimum of one and a maximum of five). An example of a farmer-annotated soil map is presented in Figure 1, where farmers identified four soil types in the village: sandy, clay/red, sandy and stone, and mixed (sandy, clay, and stone). Soil type names make it clear that farmers identify and categorize village soils according to texture and/or color.[20]

On average, there are seven plots in each of the soil types across all villages described during the mapping exercise (the standard deviation is five). However, there is substantial

[17] Table A.1 in the appendix shows similar statistics of the larger sample of 250 villages from the ISFM impact evaluation (to compare our smaller sample to a larger sample of farmers from the same geographic region of Malawi for external validity). We note that there are fewer women farmers in this larger sample, which can be attributed to our experimental design. The household head's age, education, and marital status are similar though to those of farmers included in our sample.

[18] This distinction between the physical, more observable attributes on the one hand and the chemical, less observable (that is, without testing) properties on the other hand is also standard in soil sciences (Weil et al., 2003).

[19] Depending on values for N, P, K, and S, fertilizer recommendations included 50 to 100 kg/ha of NPK fertilizer with specific mix recommendations (23:21:0+4S or 23:10:5 +6S+1.0Zn), SSP, CAN, and MAP or DAP. Liming was recommended for soils with low levels of pH. Most recommendations also included suggestions to apply organic inputs such as tobacco pellets if available, manures, crop residues, and to integrate legumes in the farming system to improve soil organic matter.

[20] In this the farmer-identified types bear some relationship to the taxonomies used by soil scientists (FAO, 2019*b*).

heterogeneity across villages. One village identified a single soil type including all plots of the 20 participant farmers. Eight villages identified two soil types: in several of these villages the 20 plots are roughly equally split between soil types, while in some villages, the split between two soil types is less equal.

In addition, for each plot chosen in the experiment, we asked farmers "how similar is the soil of this plot [chosen for soil analysis] to yours?" We framed this question to capture this dimension of soil type, and similarity in soil types, as perceived by the farmers.

4.1.2 Soil fertility

We collected soil samples from five plots in each village for soil analysis. These samples were tested for soil pH, electrical conductivity (EC), and levels of a range of macro nutrients including carbon and sulfur. Figure 2 presents the histograms of pH, EC, active carbon, sulfur, phosphorus, and soil texture for all 150 of our soil tests in the 30 study villages; Table A.3 in the appendix shows the summary statistics for these variables. Sampled plots exhibit considerable variation in these measures. Soil pH and active carbon exhibit broad evidence of soil deficiencies and, importantly, considerable variation across the optimal threshold. This means that some plots need remediation while others are in an adequate range. For example, only 46% of plots are within optimal range in terms of pH (average of soil pH is 5.6) and 38% of plots are above the critical value for active carbon (average level is 315 mg/kg), suggesting that information on these characteristics might be more valuable to farmers.

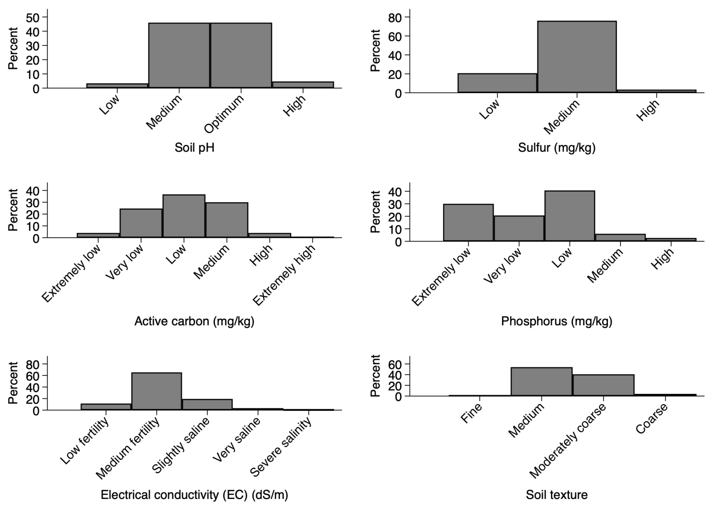
Table 1 (panel B) summarizes farmer-reported soil fertility of our sample. Almost all farmers (97%) noted that having a soil test from their plots would be very useful. The majority of farmers (62%) state that soil fertility on their primary maize plot is poor. 63% of respondents report soil erosion to be an issue, 65% report nutrient depletion, and 30% report the presence of water logging on their primary maize plot.[21]

4.1.3 Measures of soil similarity

We have two direct measures of plot similarity as perceived by farmers. First, we know whether the farmer's own plot is in the same village-type category as the plot chosen for soil

[21] These numbers are consistent with the data from the ISFM impact evaluation study (Table A.1) where farmers reported that 38% of primary plots have degraded soils, and that 50% of plots have poor or average soil fertility. In Maertens, Michelson and Nourani (2021) we also have data on the knowledge farmers have about practices to improve soil fertility and show that farmers have some familiarity with when and which fertilizer to use, how to practice mulching, and how to use cover crops. The average of a knowledge index, computed using these data, is 3.6 (out of 6), indicating a need for information about inorganic and organic fertilizers and their use. We also asked farmers to reflect on how they assess soil fertility, with many reporting to use crop yields as a proxy for soil fertility (Maertens, Michelson and Nourani, 2021). As noted, farmers distinguish the soil type, described by color and texture, from the soil's fertility. They do not treat soil type as mapping directly into soil fertility; within a given village soil type, farmers reported a range of soil fertility levels. In particular, most farmers reported that their soils were poor, regardless of the type.

Figure 2: Soil heterogeneity in the study area.



Notes: Soil samples from five plots in each of the 30 study villages. Soil variable categories from the ISFM impact evaluation study. Summary statistics for these key soil variables are presented in Table A.3 in the appendix. *Source:* Authors' calculations based on the soil analysis data.

test in the experiment according to the village mapping exercise. Second, as noted earlier, we have the farmer's own private assessment of the degree to which her plot is similar to a plot chosen for soil test as elicited in the survey during the experiment.

We observe based on the mapping exercise whether the soils "match" and compare this match with the farmers' answer in Table 2. About 43% of farmers reported that the soil of the plot chosen for soil test in the experimental round was almost the same or similar to their own, but many of these are plots that are of different types according to the soil type classification. For example, farmers classified 51% of the plots chosen in the experiment that matched the mapped soil type of their own plot as "not at all similar" and 39% of the plots chosen in the experiment that did not match the mapped soil type of their plot as "almost the same" or "somewhat similar."[22]

Table 3 shows the correlation coefficients for our various measures of soil similarity. For instance, the correlation between soil type from the map and soil type as elicited by the soil similarity question from the survey as discussed above is positive but small: 8%. Another plausible proxy for soil similarity is the Euclidean distance between plots. Using the plot locations on the maps we compute the distance (in kilometers (km)) between most plots (barring the 2% of plots located outside of the map).[23] Farmers may take distance as a

[22]This might be because the survey question conflates soil type based on texture and color with the unobservable fertility characteristics – see Table A.4 in the appendix.

[23]We calculate the distance between plots using the locations the farmers indicated on the map during the

Table 2: Soil similarity across two dimensions.

How similar is this soil to yours?	Same soil type from map 0	1	Total
My plot	0	120	120
Almost the same	395	474	869
Somewhat similar	56	53	109
Not at all similar	739	557	1,296
Don't know/no opinion	3	3	6
Total	1,193	1,207	2,400

Notes: The sample includes all observations across four rounds.

Table 3: Correlation coefficients for main independent variables.

	(1)	(2)	(3)	(4)
	Distance to plot selected (km)	Same soil type from map (=1)	Same soil type from survey (=1)	Belongs to family/ friend (=1)
Distance to plot selected (km)	1.0000			
Same soil type from map (=1)	-0.3761	1.0000		
Similar soil from survey (=1)	-0.0755	0.0805	1.0000	
Belongs to family/friend (=1)	-0.1499	0.0568	0.2197	1.0000

Notes: N=1,671. The sample includes observations for which all soil heterogeneity measures are available. Observations for farmers' own plots are excluded.

proxy for these underlying drivers of soil similarity, which could be related to either the observable characteristics or the unobserved fertility (and possible spatial correlations in management associated with geography, micro-climate, and geology). Table 1 (panels B and C) shows an average distance of 0.6 km, while Table 3 notes a negative correlation of -0.37 with the plot type indicated on the map and a negative correlation of -0.07 with the soil similarity as elicited in the survey.[24]

4.2 Social connections

Soil tests from the plots of other farmers could also be relevant to a farmer if the farmer is socially connected to the plot's owner. Table 1 (panels C and D) shows that respondents reported that about a third of the selected plots in the experiment "belongs to a family

mapping exercise. We recognize that these distances are, therefore, calculated with a degree of error. For the subset of plots where we took soil samples, we also have geographic coordinates taken by the SoilDoc app on a smartphone. For these 141 plots the median difference between the location indicated on the map and the location implied by the SoilDoc app is 612 meters. Since both sets of coordinates carry some measurement error, we treat the distance measure as our third proxy of soil similarity and interpret the results that use this measure with a degree of caution.

[24] Our survey also asked about the soil color and soil texture of the farmer's primary maize plot. We do not use these data: due to the open nature of this question, we have a large number of different terminologies.

and/or friend."[25]

This single network connection question (per farmer and per round), however, does not capture the full network of the farmer, i.e., all the contacts who could benefit from the information provided. In effect, it is likely that among all farmers who could benefit from the soil test, a subset is socially linked up to the farmer. This implies that individual-level regressions using this information will be of limited use and applicability.

4.3 Contributions to the soil test

The average contribution towards a soil test from a village plot, or willingness-to-pay (WTP) for a soil test, is 45% of one's endowment in experimental rounds 1 through 3 (panel C of Table 1). 45% corresponds to 900 MK or 1.3 $US, and is in the range of the mean WTP for a local soil test in Kenya (0.2-4.8 $US) found in Fabregas et al. (2019). Contributions to a soil test from own plots is 46% across all four rounds (panel E of Table 1 and Figure A.3).[26] In all but three village-rounds, total contributions exceeded the cost of the soil test (Figure A.4 in the appendix shows a histogram of the total contributions in all rounds and villages, with a line at 7,000 MK indicating the cost of the soil test).

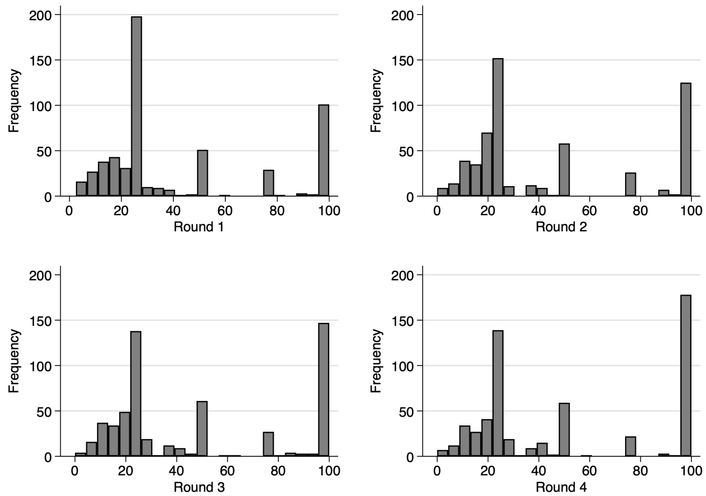
Figure 3 shows the histogram of individual WTP. Across the rounds, the majority of the farmers contribute either close to 50% or 100% of their endowment. This is consistent with the literature on public goods games; 50% is often a focal point, and few participants contribute zero (Ledyard, 1995; Chaudhuri, 2011; Vesterlund, 2017). With 20 participants in each village, 350 MK (about 17% of the endowment) represents the exact amount each farmer would have to contribute if the total cost of the soil test were to be split equally across farmers; the majority of farmers contribute well above this cut-off.[27] We note a trend of an

[25] While we allowed the farmers to specify the nature of the close relationship with the plot owner, only few chose the option "friend" (which likely has to do with the way this question was translated and may not reflect the actual friendship relations). In the appendix Table A.5 we present the relationship between the answer to the survey question "how similar is the soil of this plot [chosen for soil test] to yours?" and the question "does this plot [chosen for soil test] belong to a family member and/or friend?" A large number of plots are reported as similar but do not belong to a family member and vice versa. This indicates that there is sufficient variation across these two dimensions in order to study their respective roles (note also the correlation coefficient of 0.21 in Table 3).

[26] In order to benchmark our findings to previous literature, we followed the Random Lottery Incentive System (RLIS) method used in Kenya by Fabregas et al. (2019) (and described in Fabregas et al. (2015)) and adapted parts of their script to fit the design and location of our study. We interviewed six individuals, randomly chosen from the agricultural census lists, in four additional villages in Kasungu and Dowa. Each participant received 500 MK for participation plus a soil test or payout depending on the outcome of the RLIS. Of the 24 farmers in this sample, 9 always chose the soil test, 7 always opted for money, while 4 farmers switched from money to a soil test (4 responses were inconsistent). Our results here suggest an individual WTP for a soil test from farmer's primary maize plot of at least 2,400 MK (or 3.4 $US).

[27] We observe only 14 zero observations, across 7 farmers. While no participant contributes zero in all four rounds, there is suggestive evidence that three of these seven farmers might have misunderstood the instructions, as they contributed zero in rounds 2 through 4. This suggests that after having contributed in round 1 they might have assumed they had no funds left. This was a common error in pre-testing which we

Figure 3: Individual contributions (as % of endowment) by round.



Notes: Observations for farmers' own plots are excluded.

increasing number of farmers contributing 100% over the rounds, with a noticeable jump in the fourth round. In the empirical analysis, we include round fixed effects to control for these positive, but small in magnitude order effects. We interpret the order effects between rounds 1 through 3 as evidence of learning about the game set-up (similar increase in average contributions in later rounds is reported in Turiansky (2017)). As we do not reveal the results of the previous rounds in between rounds, the commonly found order effect of decreasing contributions as one learns about the free-riding behavior of others does not apply here.

In Table 4 we describe the patterns in changes of WTP across farmers. 24% of farmers always contribute the same amount: 12% always contribute 100%, suggesting that for them the value of the soil test always exceeds (or is equal to) their endowment; the remaining 12% appear to value the soil test independently of the plot selected (believing there is not enough heterogeneity, or not having understood the experiment). About 70% of the farmers change WTP across rounds. It is these farmers who provide the defining variation in the data which allows us to understand the role of soil heterogeneity.[28]

Finally, we note that the average contribution to a soil test is 52% in round 4 when the farmers collectively select a plot of their choice for testing (panel C of Table 1), significantly above the average contribution (45%) in previous rounds. While order effects might play a

did our best to avoid through instruction in the main experiment.

[28]Table A.6 in the appendix presents descriptive statistics on the WTP, conditional on whether or not farmers perceive their plot's soil to be similar to the soil of the plot selected for soil testing. On average, the amount contributed is higher when farmers report that the soil to be tested is the same as or very similar to their own.

Table 4: Within-farmer change in contributions across random rounds.

	(1)	(2)	(3)
	Freq.	Percent	Cum.
Same WTP: max	73	12.17	12.17
Same WTP: > 0	121	20.17	32.33
Change WTP: average < 350	54	9.00	41.33
Change WTP: average ≥ 350	352	58.67	100.00
Total	600	100.00	

Notes: Contributions (WTP) to farmers' own plots are excluded from the calculations. Data from the three random rounds only. There are 14 observations with zero contributions across 7 farmers. No farmer contributes 0 in all rounds. None of the zero contributions are towards own plot.

role, the difference is significantly larger than the previously observed order effects and is statistically significant at the 1% level. We return to this matter in the conclusion.

5 Individual-level estimation

5.1 Regression specification

We use the standard experimental framework for analysis of the individual-level data.[29]

Denote the contribution (as a percentage of endowment) to the soil test of individual i in village j in round k as c_{ijk}. Let S_{ijk} be a measure of soil similarity (in soil type) between the plot selected for soil test and i's plot. We estimate the average return to this similarity through the following regression model, using the data from the first three (random) rounds of the experiment:

$$c_{ijk} = \alpha_0 + \alpha_1 S_{ijk} + R'\alpha_2 + X'_{ij}\alpha_3 + e_{ijk}, \tag{1}$$

where R is a vector of dummy variables indicating the round to control for order effects, X_{ij} include respondent's gender, age, marital status, years of formal education, land ownership, and land rental in the last season, and e_{ijk} is an error term, clustered at the farmer's level.

We use the following measures for S_{ijk}: distance (km) to plot selected for soil test from individual i's plot, $= 1$ if individual i's plot and the plot selected for soil test belong to the same soil type as indicated on the map during the group's discussion, $= 1$ if individual i's plot and the plot selected for soil test have a "similar soil" as indicated by individual i during the survey when collecting contributions. When soils are more similar as reflected through S_{ijk}, farmers' valuation of the test is expected to increase, and, disregarding any strategic considerations (to which we will return in the village-level section), might push the contribution upwards.

[29]This individual-level analysis follows our pre-analysis plan registered in the AEA RCT Registry with the unique identifying number "AEARCTR-0004717."

Using information on the social connections, we estimate the following equations:

$$c_{ijk} = \beta_0 + \beta_1 N_{ijk} + R'\beta_2 + X'_{ij}\beta_3 + e_{ijk}, \tag{2}$$

$$c_{ijk} = \beta_0 + \beta_1 S_{ijk} + \beta_2 N_{ijk} + \beta_3 S_{ijk} * N_{ijk} + R'\beta_4 + X'_{ij}\beta_6 + e_{ijk}, \tag{3}$$

where N_{ijk} captures the social connection between individual i in village j in round k and the owner of the plot selected for soil test in village j in round k.

While the result of this specification is of interest, it does not provide us with a measure of the full network impact.[30] Yet, we expect farmers to contribute more to a soil test from a plot of a family member or friend, either because farmers are more familiar with soils and management practices of their close relations and can learn more from them, or because they feel more altruistic towards close relations, and perhaps even expect a financial reward.

As the main variables of interest, S_{ijk} and N_{ijk}, are randomized over the rounds, we estimate Equations 1-3 using a random effects specification. We report the results of a fixed-effects estimation in the appendix.[31] In all regressions, we exclude observations in which individuals report contributions to a soil test from their own plot. In an extension, we restrict the sample to farmers who change their contributions from round to round; in essence, this is the subset of farmers who respond to the randomized design of our experiment. We also present a split-sample analysis (splitting the sample between farmers with average individual contribution below 350 MK or greater/equal 350 MK).

5.2 Main results

Columns (1)-(3) in Table 5 show the results of estimating Equation 1, using the three different measures of the similarity (in soil type) between the plot selected for soil test and individual i's plot, a random-effects specification with demographic and land controls, and round fixed effects, and data from the first three rounds where plot for soil test was chosen at random.[32] The dependent variable is individual contribution as percentage of 2,000 MK endowment.

Individual contributions vary in the hypothesized manner. As similarity with the selected plot increases (as distance between plots decreases), the average contribution increases (column (1)), although this coefficient is not statistically significant. Farmers contribute 2.2 percentage points more when they categorized the soil selected for soil test and the soil from their own plot as the same soil type on the map (column (2)). Farmers also contribute 4.5

[30] The relevant social network variable from a theoretical perspective is the number of network links for whom the soil test provides useful information. We did not collect this variable in our survey. Instead, we only have the network link between the farmer and the farmer whose plot was selected for the soil test.

[31] We perform a Hausman (1978) test and find support for the random effects model.

[32] Table A.7 in the appendix shows estimated coefficients on included demographic and land controls.

Table 5: Impact of the within-village heterogeneity on farmers' individual contributions.

	Contribution to soil test as percentage of 2000 MK				
	(1)	(2)	(3)	(4)	(5)
Distance to plot selected (km)	-1.023				
	(1.530)				
Same soil type from map (=1)		2.166*			
		(1.179)			
Similar soil from survey (=1)			4.478***		2.359
			(1.317)		(1.643)
Belongs to family/friend (=1)				3.226*	-0.769
				(1.691)	(2.275)
Similar soil from survey X Belongs to family/friend					5.751**
					(2.801)
Constant	35.48***	33.52***	32.63***	33.44***	32.75***
	(6.116)	(6.076)	(6.082)	(6.107)	(6.141)
Observations	1,671	1,710	1,710	1,710	1,710
Number of farmers	593	600	600	600	600
Overall R-squared	0.0324	0.0312	0.0381	0.0327	0.0383
Mean of dependent variable	44.96	44.96	44.96	44.96	44.96

Notes: Random-effects model with round fixed effects. Controls include: respondent's gender, age, marital status, years of formal education, land ownership, and land rental in the last season. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Data from the random rounds only. Table A.7 in the appendix shows the same estimation without controls and with controls while displaying the coefficients on controls.

percentage points more when their plot and the plot selected for soil test have similar soil as indicated by the farmer during the survey when collecting contributions (column (3)). This suggests that the farmers' higher valuation for a soil test for soils of similar types outweighs any possible increase in free-riding.

Considering the coefficients on the other covariates, we note that older, female farmers appear to contribute more and farmers with more land contribute less (Table A.7 in the appendix). This is inconsistent with the literature where women are often found to contribute less and wealthier participants more. But it should be kept in mind that these might not be causal, and refer to this specific context of soil investment and improvement (for comparative studies, see, among others, Henrich (2004); Nourani, Maertens and Michelson (2021)).

5.3 Robustness checks

These results stand up to two robustness checks. In the first robustness check we alter the specification. We show results of estimating Equation 1 without demographic controls in Table A.7 and with farmer fixed effects specification in Table A.8. Coefficients are similar in both cases.

In the second robustness check, we alter the sample, while repeating the analysis for one measure of distance (= 1 if individual i's plot and the plot selected for soil test have similar soil as indicated by individual i when collecting contributions) in the appendix Table A.9. Column (1) repeats column (3) from Table 5 to provide a comparison point for the other columns. Column (2) restricts the sample to 70% of farmers who change their contributions from round to round (see Table 4). As expected, the relevant coefficient estimate now increases from 4.5 to 5 (and is still statistically significant at the 1% level). Columns (3) and (4) restrict the sample to farmers with average individual contribution below or greater/equal to 350 MK, respectively (which is the level at which the costs are equally distributed between farmers). The observed result in column (1) appears to be driven by farmers who, on average, contribute more than 350 MK. This suggests that those who are driving the treatment effect might also be those who are less financially constrained.

5.4 Role of social connections

In column (4) of Table 5 we show the results of estimating Equation 2 with the indicator variable equal to one if the plot selected for soil test belongs to a family member or friend. When the selected plot belongs to a family member or friend, the contribution increases by, on average, 3.6 percentage points (significant at the 10% level). This increase can be due to altruism, an expectation of a financial benefit, or, perhaps, even an expectation that the information will be of more use. Recall, however, that not all elements of altruism or expected gifts/loans are captured, as many others in the village might benefit from the information presented.

In order to distill the information channel, we present, in column (5) of Table 5, the results of estimating Equation 3 that includes an interaction effect of the social network variable with the variable equal to one if the plot selected for soil test has a similar soil according to the survey. An estimated cross-interaction effect is 5.7 percentage points (statistically significant at the 5% level), and the probability that the sum of the three coefficients including the interaction effect is zero is very low (with χ^2 13.34), indicating the importance of these links. This suggests that this information effect might be important and that farmers, being more familiar with soils and managements practices of their close relations, expect to learn more from the soil test from their relations' plots, especially when soils are perceived to be similar.

6 Theoretical framework

Our individual-level estimation cannot shed light on strategic behavior and free-riding. The estimated relationship between perceived similarity and farmers' contribution in effect includes the expected contributions of other farmers in the village. We now, therefore, develop a theoretical framework to conceptualize the relationship between soil characteristics and equilibrium responses.

Our model reflects the fundamentals of the experiment. Assume that each farmer is endowed with a plot of a specific soil type. This soil type is known by the farmer and by the other farmers in the village. For each soil type, optimal fertilizer use maximizes the yield. For the sake of simplicity, we assume a single (pure nitrogen) fertilizer – urea – as in, for instance, Conley and Udry (2010).[33] Soil type and fertilizer jointly determine agricultural yields. The optimal level of fertilizers is not known with certainty by any farmer, although beliefs exist and are influenced by the soil test we offer in our experiment. During the experiment, each farmer decides on her contribution for this soil test, knowing that other farmers do so as well. The ensuing Nash equilibrium depends on the distribution of soil types in the village.

6.1 Model set-up

We set up a model for one representative village. Farmers in this village are denoted by subscript i.

Soil types There are a total of T soil types. Of each soil type t, we have n_t plots in the village, with the total number of plots adding up to the total number of farmers in the village, N. We assume that farmers know their own and each other's soil type (Payton et al., 2003; Dea and Scoones, 2003; Berazneva et al., 2018).

Fertilizer and yield We denote the attainable yield by μ_t.[34] The subscript t indicates

[33] This soil type dependency of optimal levels of fertilizers has been well recognized by agronomists and economists; see, among others, Marenya and Barrett (2009).

[34] The word "attainable" follows the agronomic nomenclature: the maximum crop yield under farm circumstances.

that this yield is soil-type dependent. Production requires the use of urea fertilizer. The correct amount depends on the soil type t. If inaccurately applied, farmers incur a *knowledge penalty* as in Foster and Rosenzweig (1995).

θ_t^* indicates the optimal amount of fertilizer required for soil type t. If the farmer applies input θ_t instead of θ_t^*, she incurs a (per-unit) loss equal to $-(\theta_t - \theta_t^*)^2 < 0$ for all $\theta_t \neq \theta_t^*$. This set-up follows the optimal-input model, as in, for instance, Conley and Udry (2010).

Beliefs about the optimal fertilizer use Farmers do not know this optimal amount of fertilizer. This is the object of learning from the soil test offered by our research team during the experiment. We denote the soil test by s_t, where $s_t = 1$ implies a soil test on soil of type t was conducted, and $s_t = 0$ implies that no such soil test was conducted. While θ_t^* is unknown, each farmer has a belief of what it might be. Let this belief, $\hat{\theta}_t$, be drawn from a normal distribution, centered around the true value (θ_t^*), with variance $\sigma_{\theta_t}^2$, dependent on soil type, s_t:

$$\hat{\theta}_t \sim N(\theta_t^*, \sigma_{\theta_t}^2(s_t)) \mid s_t \in \{0, 1\}, \tag{4}$$

implying the beliefs are unbiased. The farmer's belief depends on whether or not a soil test was performed on a plot of soil type t. In particular, we assume that beliefs are more precise if a soil test was performed (compared to the situation where no soil test was performed):[35]

$$\sigma_{\theta_t}^2(s_t = 1) < \sigma_{\theta_t}^2(s_t = 0). \tag{5}$$

Value of soil test When the farmer's belief over the target fertilizer input is imprecise, the knowledge penalty is large in expectation ($E[(\theta_t - \theta_t^*)^2] = \sigma_{\theta_t}^2(s_t)$) – and as the farmer gains knowledge through soil testing, her knowledge penalty decreases in expectation. Hence, the value of the soil test reflects the difference in these variances, or:[36]

$$V_t = \sigma_{\theta_t}^2(s_t = 0) - \sigma_{\theta_t}^2(s_t = 1). \tag{6}$$

Willingness-to-pay (WTP) In each round of the experiment, the farmer reports her

[35]Note also that the initial beliefs depend on the distribution of the soil types in the village. If soils are of the same type in the village, farmers might learn more from each other over time as they experiment with various levels of fertilizers. If soils types are more diverse, farmers might learn less from each other and social learning is limited. This follows Munshi (2004) and Behaghel, Gignoux and Macours (2020). We assume that these initial beliefs are known, i.e., they are "common knowledge" in our model. This allows for tractability. An alternative specification would allow for unknown prior beliefs, i.e., soil types, and would require the specification of an optimal strategy for each type of participant, resulting in a Bayes Nash Equilibrium. We also ignore any further heterogeneity in the initial beliefs, due to, for example, differences in education, credit access, or years of farming experience.

[36]Note that the current set-up defines the value of the soil test for a soil of another type as zero. This assumption could be relaxed, but would not yield any substantially different results.

contribution or WTP. This WTP might vary from round to round, and depends on the farmer's soil type and the soil type of the plot selected for soil test. When considering the choice of the farmer, we assume that each farmer is mainly interested in maximizing yields; and hence we ignore output and fertilizer prices in our model. In effect, the only cost to applying the optimal level of fertilizer is an information cost.[37]

Payoff Assuming that a farmer will always select $\theta_t = \hat{\theta}_t$ to minimize square loss in expectation, the expected payoff of a farmer i with soil type t, $P_{i,t}$ depends on whether or not a soil test is conducted:

$$P_{i,t} = \mu_t - \sigma^2_{\theta_t}(s_t) - WTP_{i,t} + R_i, \tag{7}$$

where R_i refers to the rebate. Recall that the soil test was provided only if the total of the contributions was equal or exceeded the cost of the soil test. This cost was set to be identical to the actual variable cost of the soil test and known to the farmers. Denote by C the cost of the soil test. We hence have:

$$\sum_{\forall i}[WTP_{i,t} - C] \geq 0 \;\Rightarrow\; s_t = 1. \tag{8}$$

If the total of the contributions exceed C, the experimenter refunds the farmers. The amount of this refund is proportional to the initial contribution, or:

$$R_i = \frac{WTP_i}{\sum_{\forall i}[WTP_i]} \sum_{\forall i}[WTP_i - C]. \tag{9}$$

Choice of WTP Each farmer chooses her WTP as to maximize her expected payoff as defined in expression (7). This WTP can take any value upwards from zero.

In the case that the soil selected to be tested is not of the same type as the farmer's, the farmer's optimal WTP equals zero, since, effectively, there is no private gain (this appears consistent with the results in Section 5). There is a second scenario in which one might end up paying nothing: when the soil test is not conducted because the total contributions are smaller than the cost C. To understand if and when such a scenario might arise, one needs to consider the individual contribution of a farmer as part of the equilibrium strategy.

[37] We recognize that this assumption is not realistic (Michler et al., 2019), but it is sufficient to explore the relationship between soil heterogeneity and contributions in the experiment. In doing so, we effectively ignore credit constraints, which might affect the contribution to the soil test (as in Tamim et al. (2020)). See also Banerjee and Duflo (2010) for studies on willingness-to-pay for fertilizer and credit constraints.

6.2 Nash equilibrium

The solution to this problem takes the shape of a Nash Equilibrium in which each farmer maximizes her expected payoff, knowing that other farmers (within the same soil type) do so as well. This Nash Equilibrium is defined as a vector $(WTP_1^*, WTP_2^*, ..., WTP_N^*)$, such that, $\forall i$ WTP_i^* is a best response to others:

$$P_i(WTP_1^*, ..., WTP_i^*, ..., WTP_N^*) \geq P_i(WTP_1^*, ..., WTP_i, ..., WTP_N^*). \tag{10}$$

To derive the equilibrium, it is helpful to start with the efficiency question: When is it efficient to provide the soil test? We can distinguish three cases. In Case (1), the aggregate value of the soil test equals the cost of the test. In Case (2), the aggregate value of the soil test strictly exceeds the cost of the test, and, in Case (3), the aggregate value is strictly lower than the cost of the test. The efficiency condition entails that the test *should* be provided if the total value (weakly) exceeds the cost: provide the soil test in Cases (1) and (2), but not in Case (3). In this section, we only work out the most likely case, Case (2) (and develop Cases (1) and (3) in the appendix).[38] We also ignore the unlikely scenario in which the value of the soil test for a single farmer exceeds the cost of the soil test to exclude the trivial case in which one farmer purchasing the soil test on her own constitutes a Nash Equilibrium.[39]

Let us start with the simplest scenario: all farmers contribute zero and no soil test is provided. This constitutes a Nash Equilibrium. To see this, note that if one farmer were to consider contributing a positive amount, the soil test would still not be provided, and the farmer simply reimbursed her contribution.

Consider now the option where all farmers contribute their valuation. In this scenario, the collective contribution exceeds the cost of the soil test, i.e., one has excess. Hence, each farmer is incentivized to slightly lower her contribution. If a farmer reduces her contribution by a small amount, her refund would decrease, but not to the extent of her reduced contribution, and overall, her payoff would increase (and she would still receive the soil test). Hence, contributing one's valuation is not a Nash Equilibrium.

Is there no equilibrium in which the soil test is provided? Imagine a scenario in which a subset of farmers contributes their valuation, with the total adding up to the cost of the test, and the others contributing zero (which, for some, might be their valuation). In this case, no one has an incentive to deviate. The non-contributors will not be inclined to contribute, as doing so will decrease their value. And the contributors too will not be inclined to contribute less, as by doing so, the soil test would no longer be provided. In effect, there

[38] With a relatively low cost of the soil test, our experiment represents Case (2). This is consistent with Figure A.4: only in three village-rounds total contributions did not exceed the cost of the soil test.

[39] In the experiment, average contributions to soil test (as percentage of the endowment) is 46%.

is an infinite number of such equilibria possible. While all constitute a Nash Equilibrium and are (Pareto) efficient, they can be considered unfair, as some farmers free-ride on the contributions of others. In contrast, there is a single fair equilibrium. Imagine a situation in which everyone contributes a fixed share of their value, with the total equalling the cost of the soil test (note that again, for some, this share might result in a zero contribution). In this case too, no one has incentive to deviate.[40]

Which equilibrium the village would settle on, meaning which one would become a focal point, depends on the distribution of soil types in the village, and aspects related to the village's history. For instance, if farmers have a habit of coordination and cooperation, the zero contribution equilibrium seems unlikely, and the fair equilibrium, in which everyone contributes the same share of their value, might be more likely.

In Figure 4, we provide evidence on the type of equilibrium. Note that we do not know the farmers' valuations of the soil test from our survey. Hence, to test for the presence of focal equilibria in each village, we compute the coefficient of variation for each group of farmers with the same soil type within each round. If the equilibrium is fair, this ratio should be close to zero. If the equilibrium is unfair this ratio is closer to one. Prior to looking at these numbers, recall that while the zero contribution equilibrium is a (theoretical) option, it appears not one which occurred in our context (see Figure A.4). In Figure 4 we see that a significant mass of the distribution falls between 0.5 and one, indicating that, overall, unfair equilibria dominate.

However, within villages and soil types there are groups of farmers that contribute more equally. It is notable that the type of equilibrium tends to remain the same across rounds. An ANOVA analysis of the ratio of the standard deviation over the mean (shown in Figure 4) indicates that 63% of the variation is at the village-soil type level, with the remaining variation coming from variation across rounds. This means that the same set of farmers (with the same soil type within each village) tends to select a similar equilibrium, round after round in the experiment.

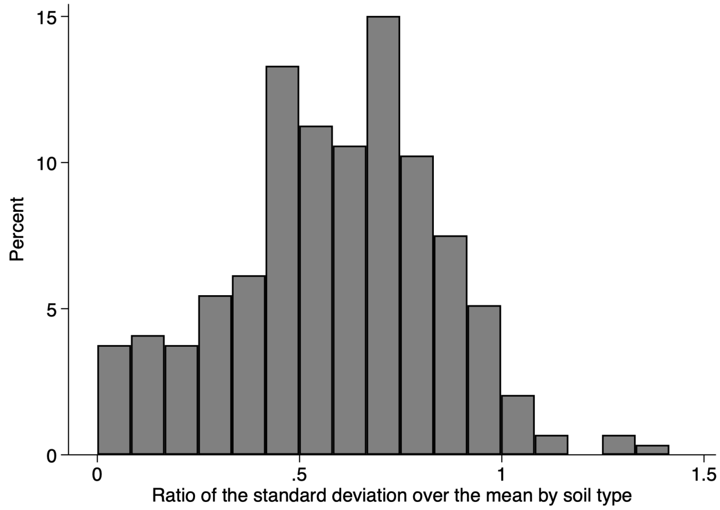
6.3 Heterogeneity in soil types

In villages with increased soil heterogeneity, the value of the soil test might be higher (as the initial variance on prior beliefs is higher due to lack of social learning within the village) as per Equation 6.

With an increased number of soil types, farmers also tend to belong to smaller groups. This might affect the group dynamics and one might be more likely to see the emergence

[40] In both types of equilibria, the aggregate contributions do not exceed the cost of the test. While this is not quite consistent with what we see in Figure A.4, there are likely other factors at work which are not documented in our model.

Figure 4: Histogram of the coefficient of variation of farmers' contributions by soil type.



Notes: Ratio is calculated at the village, soil type, round level. Soil type is defined as the soil type indicated by farmers in each village during the mapping exercise. Plots that were located outside the map are excluded from the ratio calculations, so are the observations (contributions at the village, soil type, round level) for which we have only one contribution.

of the within-type fair equilibrium, where everyone contributes in a proportionate manner, as the number of farmers within each soil type represents a smaller, more intimate group. The farmers for whom the type does not match the chosen plot's type might, however, settle on a near-zero WTP, driving the overall village-level dispersion in contributions up. With smaller groups, the zero contribution outcome becomes unlikely, as it is unlikely to be the best outcome for all farmers in any given round (as a subset of farmers would have the same soil type as the one of the plot selected for soil test), and smaller group sizes can be expected to favor some degree of cooperation.

7 Village-level estimation

7.1 Regression specification

To shed light on how village conditions relate to the overall contributions made, the patterns of these contributions, and the role of free-riding, we estimate the following between-village model, using data from all four rounds:

$$F_{jk} = \beta_0 + \beta_1 H_j + R\beta_2 + Y_j\beta_3 + e_{jk}, \tag{11}$$

where F_{jk} represents a village-round level contribution statistic and H_j measures within-village soil heterogeneity (in types). R is a vector of dummy variables indicating the experimental round to account for order effects. The vector Y_j includes village-level demographic controls similar to the controls in the individual-level estimation (share of female respondents and share of married respondents, as well as means and standard deviations of respondents' age, education (in years), land owned, and land rented). e_{jk} is an error term.

We use three statistics as dependent variable, F_{jk}. First, we use the mean of village-round contributions (as a percentage of the village-level endowment). This is the equivalent to the individual-level regression in Equation 1. Second, we use the coefficient of variation (standard deviation divided by the mean) of contributions computed from the individual contributions in each village-round. Third, we use the share of the individual contributions below 350 MK. Both two latter statistics might point towards the presence of an unfair contribution equilibrium or free-riding.

We consider the following measures of soil heterogeneity: the average distance to the plot selected for soil testing (that is, the average across all farmers), the number of soil types in each village as indicated on the map during the group's discussion, and the share of the farmers who noted during the survey when collecting contributions that their plot did not have a "similar soil" to the plot selected for testing. In addition, we make use of the results of the soil tests on the five plots we tested in each village (one collected during the experiment and four collected at a later date) and compute the coefficient of variation in soil carbon. Summary statistics are reported in Table 6.

All four measures are proxies for the heterogeneity in the village in terms of soil types. An increase in soil heterogeneity might increases the value of the soil test (as initial beliefs are more uncertain). The zero contribution outcome is no longer a best outcome for all farmers in any given round (since a subset of farmers shares the same soil type as the type of soil selected for soil test). And with fewer farmers per type, one might see both the emergence of a fair within-type equilibrium, but also an increased number of farmers contributing near-zero (as their soil type might be very different from the type of the plot selected).

In an extension, we again consider the role of social connections. For each individual, we have information on the connection with four other individuals, three of which were randomly selected. While this information is of limited use in the individual regression, at the village-level, this resembles the random-matching-within-sample technique of Santos and Barrett (2008) and Conley and Udry (2001). In effect, combining the individual-level data on social connections, we can derive a proxy measure of village social connectivity. Farmers are connected to 30% of all the contacts presented to them in the experiment (this number excludes contacts to themselves) (Table 6). We hypothesize that increased social connectivity might reduce the likelihood of the zero-contribution equilibrium arising, and might make even a fair equilibrium more likely as caring for others creates a multiplier effect

Table 6: Village-level summary statistics.

Variables	N (1)	Mean (2)	St.dev. (3)	Min (4)	Max (5)
Panel A: Measures of village contributions					
Average village-round contribution (MK)	120	933.2	345.2	284.2	1,611
Average village-round contribution as percentage of endowment	120	46.66	17.26	14.21	80.53
Variance of village-round contributions as percentage of endowment	120	0.630	0.162	0.106	0.926
Village-round share of contributions below 350 MK	120	0.153	0.119	0	0.632
Panel B: Measures of village soil heterogeneity					
Share of contributions to plots with dissimilar soil	120	0.571	0.108	0.329	0.763
Average distance to sampled plots (km)	120	0.649	0.218	0.130	1.074
Number of village soil types	30	3	1.004	1	5
Variance of soil carbon from 5 plots	30	0.296	0.120	0.121	0.565
Share of contributions to plots of family/friends	30	0.299	0.188	0	0.737

Notes: Calculations of village-level dependent and independent variables exclude observations for farmers' own plots.

by increasing the payoffs (see the derivation in the appendix).

7.2 Main results

Table 7 presents the results of estimating Equation 11, using data from four rounds and all 30 villages (for the total of 120 observations). Estimation includes round fixed effects and village-level demographic and land controls, similar to those in the individual-level regressions. Appendix Table A.10 shows estimated coefficients on all controls.

We emphasize that unlike the individual-level regressions, which build on the random variation introduced by the experiment, the village-level results should be viewed as correlations. Nevertheless, the extensive set of controls, capturing differences in the socio-economic and demographic make-up of the villages, and the inclusion of round fixed effects provide a certain degree of confidence that these relations capture some degree of causality.

Table 7: Impact of the within-village soil heterogeneity on village-round contributions.

	Mean of contributions as percentage of endowment				Coefficient of variation of contributions as percentage of endowment				Share of contributions below 350 MK			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Share of contributions to plots with dissimilar soil	-22.84				-0.268**				0.265**			
	(15.48)				(0.103)				(0.118)			
Average distance to sampled plots (km)		26.13***				-0.0373				-0.227***		
		(8.156)				(0.0876)				(0.0744)		
Number of village soil types			7.167***				-0.0318***				-0.0431***	
			(1.401)				(0.0118)				(0.0108)	
Variance of soil carbon from 5 plots				74.82***				0.335***				-0.0887
				(9.933)				(0.122)				(0.0926)
Constant	-33.58	-31.38	-12.10	-18.34	0.142	0.304	0.249	0.301	0.0927	0.0376	-0.106	-0.0551
	(35.44)	(30.96)	(34.23)	(35.48)	(0.453)	(0.431)	(0.424)	(0.391)	(0.239)	(0.199)	(0.215)	(0.231)
Observations	120	120	120	120	120	120	120	120	120	120	120	120
R-squared	0.342	0.378	0.429	0.503	0.356	0.332	0.354	0.371	0.366	0.404	0.399	0.326
Mean of dependent variable	46.66	46.66	46.66	46.66	0.63	0.63	0.63	0.63	0.15	0.15	0.15	0.15

Notes: Round fixed effects and village-level controls in all specifications include: share of female respondents, share of married respondents, mean and standard deviation of respondents' age, mean and standard deviation of respondents' education (years), mean and standard deviation of respondents' land owned and land rented. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Data from four rounds. Table A.10 in the appendix shows the same estimation, while displaying coefficients on the controls.

We present these results at the village-round level, the level at which the experiment was conducted. While we expect contributions to be correlated within soil types as per our discussion in Section 6, our goal is to explore the overall patterns in the contributions and link them up to village characteristics. Indeed, from a policy perspective, it is this relationship which is the most relevant, as extension agents will have to take into account the role of village soil heterogeneity and social connections within the village when establishing a mechanism to deliver soil information. In the next sub-section, we present equivalent results at the village-round-soil type level.

Before proceeding to the results recall that if everyone contributes all their endowment to the soil test, we would have a total village contribution of 40,000 MK, significantly exceeding the cost of the soil test of 7,000 MK. Recall also that in all but three village-rounds, the total village contributions exceeded the cost of the soil test, and in effect, taking into account the randomized selection of the final plot to be tested, all villages received a soil test (see also Figure A.4). From Table 6 we recall an average village-round contribution of 47%.

We start with the coefficient of variation across the contributions as the dependent variable. In columns (5) through (8) of Table 7, an increase in the coefficient of variation suggests the presence of a more unequal equilibrium. From Table 6 we know that the average coefficient of variation is 0.63. As the perceptions of soil heterogeneity increase (as indicated by the share of farmers noting a dissimilar soil in column (5) and the number of village soil types in column (7)), the coefficient of variation decreases by 0.27 and 0.03 percentage points, respectively. Or, as soil heterogeneity increases, contributions become more equal.

However, a more objective measure of village soil heterogeneity – the coefficient of variation of soil carbon – returns an opposite result: as soils become more similar, dispersion in contributions increases. The flipped sign on the soil heterogeneity variable suggests that it is farmers' perceptions about soils that are driving their contributions (and confirms that farmers' perceptions do not one-for-one correspond with objective measures of soil heterogeneity). Finally, the coefficient on a less precise, but potentially also more objective measure of soil heterogeneity – average distance to sampled plots – is negative but not statistically significant.[41]

Let's now turn to the mean of village-round contributions (as percentage of endowment) in columns (1) through (4) in Table 7. The share of the farmers who noted (during the survey) to have a dissimilar soil appears not to be (statistically significantly) related to the mean village contribution (column (1)). The three other measures of within-village soil heterogeneity give statistically significant (at 1% level) results. As the average distance to the plot selected for soil testing increases, the number of village soil types as indicated on the map increases, and the coefficient of variation in soil carbon increases, so do the average contributions – by 26.1, 7.2, and 74.8 percentage points, respectively.

[41] An alternative measure to capture free-riding at a village level is to compute the share of contributions below 350 MK. 15% of individual contributions (excluding observations for farmers' own plots) are below this level (Table 6). An increase in this share might relate to an increase in free-riding. For two out of four measures of soil heterogeneity, we find similar results as in columns (5) through (8). When the average distance to the plot selected for soil test and the number of soil types in the village increase, this share declines (these coefficients are significant at 1%). However, the village soil heterogeneity as measured through the survey yields an opposite result, and we find no statistical significant relationship between the measure based on soil carbon and the share of contributions below 350 MK.

Overall, these results suggest that within-village perceived soil heterogeneity increases average contributions, but decreases dispersion of village contributions and the share of contributions below 350 MK, suggesting that while averages go up, free-riding goes down, and one can expect the emergence of a fair equilibrium.

7.3 Results by soil-type

When conducting the analysis at the village-level, we consider several mechanisms through which soil heterogeneity affects contributions.

Results from the theoretical model suggest that the value of the soil test might be higher in villages with increased soil heterogeneity, as the initial variance on prior beliefs is high to start with due to the lack of learning opportunities in such a village. This might, disregarding any strategic interactions, push up the average contribution in the village. Considering strategic interactions, with an increased number of soil types, farmers belong to smaller groups, which might further push up the average contribution. On the other hand, there is an increased chance for any given farmer that the soil test selected might not match their type. Looking at the results in Table 7 it appears that the first two channels dominate. As spatial soil heterogeneity increases, farmers contribute more to acquire the soil test.

In Table A.11 in the appendix we exclude this last channel of influence, and relate the number of farmers in each village-level soil type category to the village-soil type-round contributions. We limit the sample to village-level soil type-rounds when the soil type as indicated by the mapping exercise matches the soil type of the plot selected for soil testing ($N = 114$). Column 2 suggests that as the number of farmers within each type-group increases so does the coefficient of variation, consistent with the results above (the sample size appears insufficient to draw conclusions on the mean and share below 350 MK). This is reassuring as an increase in soil types in a village does not necessarily mean an equal-sized decrease in number of farmers in each of the soil-type groups.

As noted in section 4, on average, there are 7 farmers (plots) in each of the soil types across all villages identified during the mapping exercise; however, some village-level soil types have only one farmer, while others have 20 – there is substantial heterogeneity.

7.4 Role of social connections

In the appendix Table A.12 we explore the relationship between social connections and village-level contribution statistics. We find that as the village becomes more socially connected (based on our limited measure), the dispersion of village contributions (as measured by the coefficient of variation) decreases – the contributions become more equal (column (2)). We, however, note no statistical significant relationship between our measure of the village connectivity and the average contributions (column (1)) or the share of contributions below 350 MK (column (3)).

8 Conclusion

We conduct a public goods experiment in rural Central Malawi to shed light on the relationship between willingness-to-pay for agricultural information pertaining to soils and soil heterogeneity. Individual contributions towards a soil test from a randomly chosen plot increase with closer geographic proximity and perceived similarity between the plot chosen for soil test and a farmer's own plot. Farmers also contribute more to tests from plots of their family and friends, especially when their soils are perceived to be similar.

We use village-level analysis to further analyze farmer interactions. While heterogeneity in (soil) conditions is known to impede learning (Marenya and Barrett, 2009; Suri, 2011; Berazneva et al., 2019; Tamim et al., 2020; Munshi, 2004), the other side of the coin is that local information may become more valuable to individuals in heterogeneous environments. We show that free-riding declines as heterogeneity increases; when soil heterogeneity increases, the average contribution within a village also increases and the dispersion of contributions decreases. As soils are perceived to be less similar, both the value of the information increases to an individual farmer and the scope for free-riding decreases (Kölle, 2015).

From a policy perspective, our results suggest that agricultural information provision could plausibly be paid for through the joint contributions of a group of geographically-proximate farmers. The average individual contribution is 45% of the endowment (900 MK or 1.3 $US), implying a total village contribution of about 18,000 MK, significantly exceeding the marginal cost of the soil test of 7,000 MK. In all but three village-rounds, the total contributions exceed the cost of the soil test.

If the goal is to provide a soil test to each village, allowing the farmers to select a plot may result in greater aggregate contributions (and cover the cost of soil testing). To test this hypothesis, in the last round of our experiment, we allowed farmers to collectively determine the plot to be tested. While farmers viewed the random choice of plots for soil testing as fair, they contributed more towards tests when they were allowed to collectively decide which plot to sample. Average contributions increased to 52% of the endowment (as compared to 45% of the endowment in rounds where plot to be tested was chosen at random).

But how did farmers select a particular village plot for testing, and why might they be willing to contribute more towards it? While our sample size is limited (only 30 villages), some tentative conclusions can be drawn. First, the plot chosen is not more similar, on average, to the other plots. On average, the soil of the plot collectively chosen for soil test shares fewer similarities with other farmers' plots (compared to our random draw). Nor is the plot selected centrally located in the village.

While it could be the case that increased agency results in higher contributions, irrespective of the plot selected, we speculate, that it is the farmer, not the plot that makes a difference. We document some notable differences between the average farmer and the farmer whose plot is selected: the farmer with the chosen plot is more likely to be male, older, own more land, and belong to more farmer groups. None of the selected plots (in round 4) belong to the village head. While this does not eliminate the possibility of some degree of exerted pressure or power capture, it is notable that villages do not by default resort to choosing the plot of the village head. By choosing the plot of a more experienced, wealthier, and better connected farmer, villagers may be opting for someone who is more likely to be willing and able to implement the soil management recommendations resulting from the soil test, and share what she learned more effectively with others. In effect, selecting a first adopter carefully may counter the well-established free-riding effect in agricultural technology adoption as in Foster and Rosenzweig (1995). So-called progressive farmers or early adopters can play an important role kick-starting the adoption of new soil-improving technologies in their networks (see also Maertens (2017) and Beaman et al. (2021)).

Several limitations of our experimental design are worth mentioning and deserve future research attention. First, our evaluation was short-term, and hence, we did not establish the value of these soil tests in terms of increased productivity, yields, or profits. It is not clear how much farmers should value a soil test; yet, recent research suggests considerable private benefits, despite financial constraints related to liquidity and credit access (Murphy et al., 2020; Harou et al., 2020; Corral et al., 2020). In our setting, farmers universally reported that a soil test would be useful and, more importantly, contributed a significant amount towards the soil test. Understanding the value of a soil test to farmers is outside the scope of this paper but is obviously an important next step.

Second, while the full extent of spatial variation in soil characteristics and fertility is not known to farmers, farmers have beliefs about the degree of such variation (it is notable that our results are consistent whether we use subjective perceptions or objective (lab-based) measures of soil similarity). Two potential mismatches between what farmers believe and the underlying spatial variation are relevant: (1) the existence of minimal spatial heterogeneity in a circumstance in which farmers believe there is a lot of difference across plots and (2) the existence of considerable spatial heterogeneity when farmers believe that plots are mostly similar. Understanding the impact of these mismatches is essential for effective delivery of agricultural information and its impact on yields and farm profitability. Circumstances in which farmers underestimate heterogeneity might result in under-contribution to the soil test and overall reduced experimentation and increased reliance on social learning (Munshi, 2004). In short, information delivery (towards a discrete information good, like a soil test) through collective private contributions could prove socially optimal as long as farmers' beliefs about heterogeneity are consistent with underlying variation. Here, we take a first step in linking (perceived and objective) heterogeneity with willingness-to-pay for public information. Our results suggest that characterizing what potential users believe about the kind of public good is essential to understanding why new technologies are adopted or stall and is an important area for future research.

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Supplemental Appendix for "Private Contributions for Public Information: Soil Testing in Malawi"

A Theoretical framework

Derivation of the remaining Nash equilibria

In this section, we work out the other two, less likely, cases for Nash equilibria.

Case (1) is, perhaps, the simplest, but also most unlikely case – a scenario in which the total value of the test exactly equals its cost. In this case, it should be clear that all farmers are bidding zero so that $WTP_i = 0, \forall i$ is a Nash equilibrium. If one farmer were to consider bidding a positive amount, the test would still not be provided, and the farmer simply reimbursed their contribution. Contributing exactly one's value of the test is a Nash equilibrium as well. Deviating from this equilibrium and unilaterally bidding below one's value would result in a situation of no soil test, a loss almost equal to the value of the soil test. Bidding higher than one's value will not result in a loss of the soil test, but as the rebate will be distributed among all contributors, the gain in rebate will not compensate for the extra loss in funds paid out. It is notable that a contribution vector in which some people pay more than their value, with others paying less, while the total still equals exactly C is not a Nash Equilibrium either: anyone who pays more than their valuation is better off bidding zero. So, in this Case (1), there are two Nash equilibria: a zero contribution equilibrium and a fair equilibrium.

Case (3) is also fairly unlikely in our context. In this case also all farmers bidding zero is a Nash Equilibrium. If one farmer were to bid any positive amount, the public good would still not be provided. In effect, in this case, there does not exist a Nash equilibrium in which the soil test would be provided. Such a scenario would require at least one farmer to bid more than her value, which we already established, is not a best response. Note that in this Case (3), the equilibrium outcome and efficient outcome always coincide.

Social connectivity and social networks

The presence of social connections between villagers might complicate matters, as one, when considering the value of a soil test, will also consider the value to others one is connected to. As our data on social connections are limited, we consider a formal derivation is beyond the scope of this paper. However, in this appendix section, we present a few insights with some empirical implications.

We start with the assumption that each farmer in the village is embedded in a known social network. This social network captures family relations, altruism, and the like. The wording "known" implies that each farmer not only knows their links, but also the links of their links (an assumption which could be challenged in certain contexts; see, for example, Breza, Chandrasekhar and Tahbaz-Salehi (2018)). With N farmers in the village, this social network can be represented by an N by N matrix. We do not have data on the full matrix; instead we have information on selected cells. Denote the network connection between farmer

i and another farmer j as r_{ij}. For simplicity, we assume that this variable can take on two values, or: $r_{ij} \in \{0, 1\}$, where the value of 1 denotes that there is a connection between the two farmers, and the value of 0 denotes otherwise.

Farmers can care about the payoff of other farmers in their network, either because they directly value their welfare or because they indirectly benefit through financial networks (see, among others, Fafchamps (2011) and Dercon and Krishnan (2000)). Let's denote this degree of care as $\alpha_{ij} = \alpha(r_{ij})$. We assume that:

$$\alpha(r_{ij} = 1) > \ \alpha(r_{ij} = 0) \quad \text{and} \quad r_{ij} \in [0, 1] \tag{A.1}$$

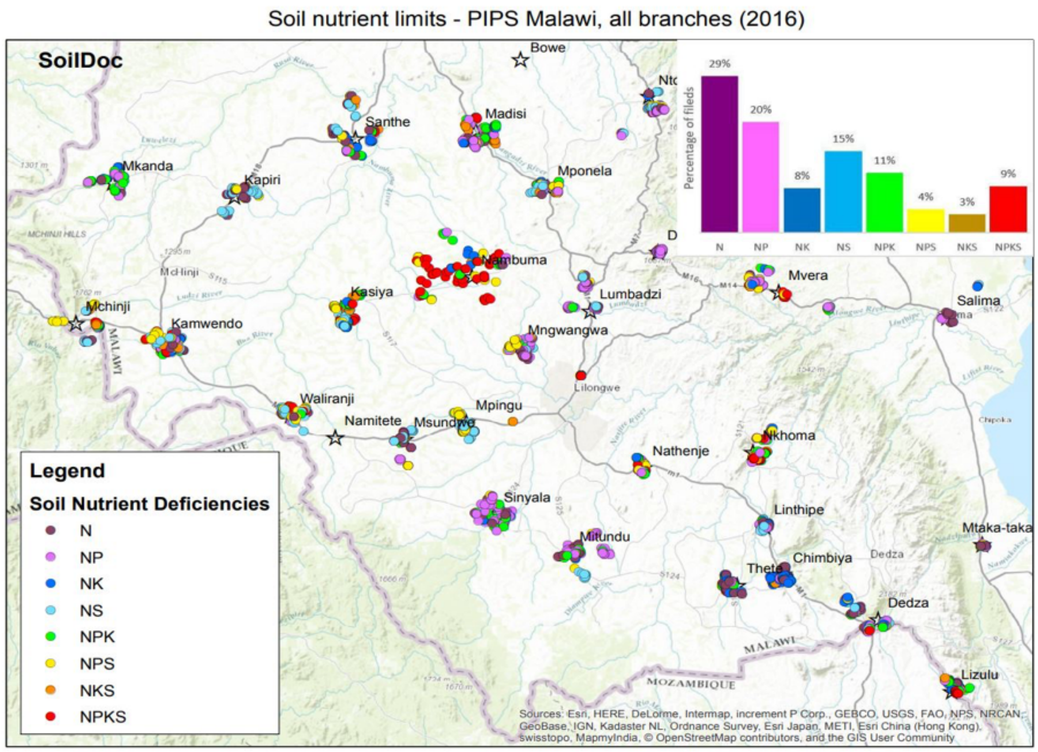
If, however, altruism is present, and, for some contacts, the soil test provides valuable information, then WTP_i might further increase.

Note that the relevant social network variable here is the number of links for whom the soil test provides useful information. We did not collect this variable in our survey. In effect, we only have the network link between the farmer, and the farmer whose soil we selected for the soil test. Hence, this implication cannot be tested using our data.

Prospects are slightly better when we consider the village as a whole, as for each farmer, we have information on the link between the farmer and four randomly drawn contacts. Aggregating these data at the village level, we can derive a proxy measure of village social connectivity. Increased social connectivity might reduce the likelihood of the zero-contribution equilibrium arising, and might make even the unfair equilibria less likely, as the α_{ij} factors create a multiplier effect by increasing the payoffs in Equation (7).

B Additional figures and tables

Figure A.1: Soil nutrient deficiencies in central Malawi.



Notes: Data (N=2,700) from the ISFM impact evaluation.

Figure A.2: The experimental timeline.

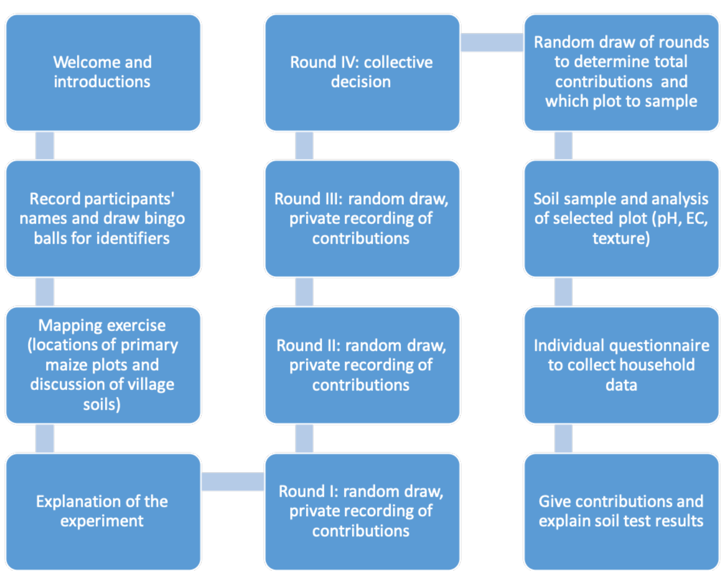
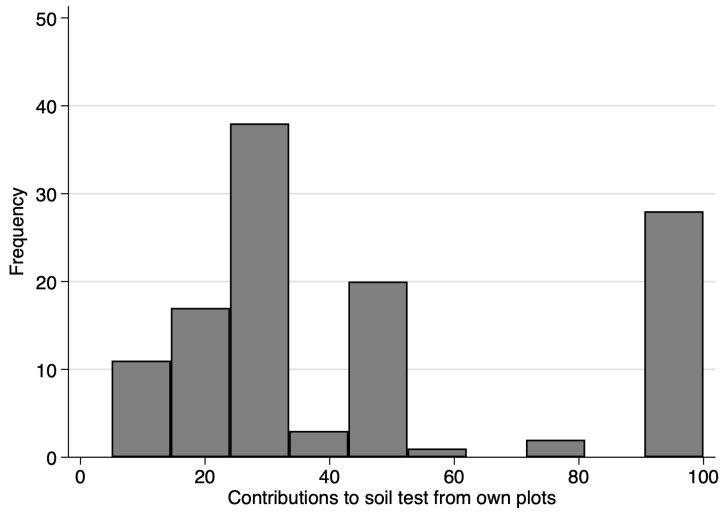
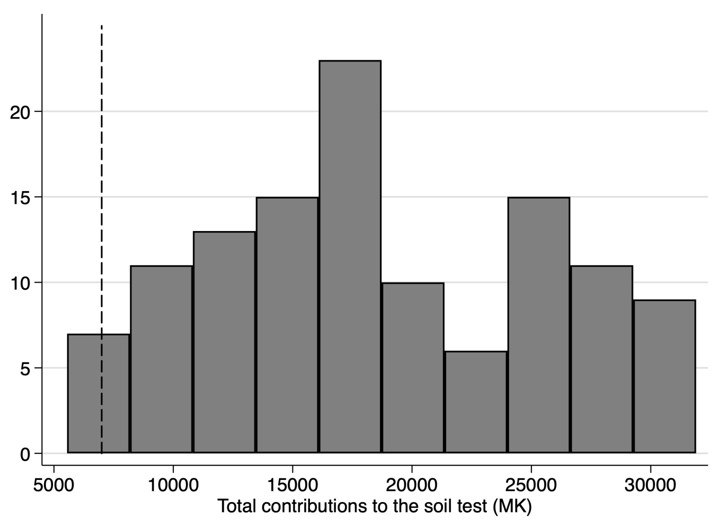


Figure A.3: Histogram of contributions to soil test from own plots.



Notes: N=120. Observations across four rounds with farmers contributing to a soil test from their own plot.

Figure A.4: Village total contributions.



Notes: Total contributions from four rounds (N=120). Only in three village-rounds the total contributions are below the cost of the soil test, which is marked at 7,000 MK with a dashed line.

Table A.1: Summary statistics of the ISFM project sample.

Variables	N (1)	Mean (2)	St.dev. (3)	Min (4)	Max (5)
Panel A: Demographics					
Household head is female (=1)	2,501	0.183	0.387	0	1
Household head's age	2,501	42.401	15.166	15	91
Household head's education (years)	2,501	4.718	3.468	0	12.5
Monogamous married (%)	2,501	72.81			
Polygamous married (%)	2,501	8.76			
Widowed (%)	2,501	7.68			
Separated/divorced (=1)	2,501	8.72			
Not married (%)	2,501	2.04			
Land owned by household (acres)	2,501	4.687	6.976	0	103.84
Panel B: Knowledge					
Knowledge index (out of 6)	2,501	3.626	1.413	0	6
Respondent finds numerical information useful (%)	2,500	52.64			
Respondent can count up to 20 (%)	2,501	96.68			
Panel C: Soil fertility and perceptions (% of fields)					
Plot's soil is very poor (=1)	3,528	2.86			
Plot's soil is somewhat poor (=1)	3,528	13.86			
Plot's soil is average (=1)	3,528	31.35			
Plot's soil is somewhat good (=1)	3,528	32.65			
Plot's soil is very good (=1)	3,528	19.27			
Soil erosion on primary maize plot (=1)	3,525	38.38			
Nutrient depletion on primary maize plot (=1)	3,521	34.82			

Notes: Panel A shows demographic characteristics for all farmers in the sample of the ISFM project (2,501 farmers). Panel B shows some evidence of farmers' knowledge of recommended agricultural practices. Knowledge index adds correct answers to six questions about recommended chemical and organic fertilizer applications and their timing. Panel C provides some evidence on farmers' soil fertility perceptions.

Table A.2: Village-level summary statistics – demographics.

Variables	N (1)	Mean (2)	St.dev. (3)	Min (4)	Max (5)
Share of married respondents	30	0.840	0.0947	0.650	1
Share of female respondents	30	0.488	0.160	0.200	0.850
Mean of respondents' age	30	39.76	4.430	33	53.10
Standard deviation of respondents' age	30	13.68	1.969	10.18	18.04
Mean of respondents' education (years)	30	5.885	1.546	2.300	9.950
Standard deviation of respondents' education	30	3.398	0.477	2.366	4.292
Mean of respondents' land owned	30	2.644	1.259	1.237	6.650
Standard deviation of respondents' land owned	30	1.914	1.652	0.548	7.087
Mean of respondents' land rented	30	0.334	0.254	0	1.150
Standard deviation of respondents' land rented	30	0.687	0.634	0	3.715

Notes: Demographic controls included in the village-level regressions.

Table A.3: Soil test results for key soil characteristics.

Variables	N (1)	Mean (2)	St.dev. (3)	Min (4)	Max (5)
Soil pH (1-7)	150	5.630	0.469	4.680	7.420
Electrical conductivity (EC) (dS/m)	150	0.252	0.196	0	1.828
Active carbon (mg/kg)	150	315.0	113.2	90.72	748.1
Sulfur (mg/kg)	150	11.41	1.999	6.434	16.19
Soil texture is fine (=1)	150	0.0400	0.197	0	1
Soil texture is medium (=1)	150	0.0133	0.115	0	1
Soil texture is moderately coarse (=1)	150	0.540	0.500	0	1
Soil texture is coarse (=1)	150	0.407	0.493	0	1

Notes: Soil samples from five plots in each of the 30 study villages. Soil variable categories are found in Figure 2.

Table A.4: Soil texture from survey and the mapping exercise.

	Same soil type from map				
Soil texture on primary maize plot	Sandy	Clay/loam	Mixed	Other	Total
Sandy	84	21	22	2	129
Clay/loam	38	92	27	0	157
Mixed	99	109	93	4	305
Other	1	0	0	1	2

Notes: The comparison of soil texture as reported in the survey (when asked about soil texture on primary maize plot) and constructed from the mapping exercise. The sample includes observations from the first round only.

Table A.5: Soil similarity and social networks.

	Plot belongs to family/friend		
Same soil type from survey	0	1	Total
0	1,010	292	1,302
1	589	389	978

Notes: The comparison of soil similarity as reported in the survey and social networks. Observations for farmers' own plots are excluded.

Table A.6: Individual WTP when soils are similar and different.

	Same soil type from survey	
	0	1
WTP mean	42.48	47.96
WTP st.dev.	32.39	34.60
WTP % zero bids	0.007	0.004
Number of observations	936	774

Notes: Contributions (WTP) to farmers' own plots are excluded from the calculations. Data from the three random rounds only.

Table A.7: Impact of the within-village heterogeneity on farmers' individual contributions (with and without controls).

	Contribution to soil test as percentage of 2000 MK									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distance to plot selected (km)	-0.647	-1.023								
	(1.513)	(1.530)								
Same soil type from map (=1)			1.924	2.166*						
			(1.177)	(1.179)						
Similar soil from survey (=1)					4.556***	4.478***			2.343	2.359
					(1.314)	(1.317)			(1.636)	(1.643)
Belongs to family/friend (=1)							3.142*	3.226*	-1.054	-0.769
							(1.689)	(1.691)	(2.259)	(2.275)
Similar soil from survey X Belongs to family/friend									6.101**	5.751**
									(2.791)	(2.801)
Respondent is female (=1)		4.922*		4.515*		4.410*		4.446*		4.490*
		(2.682)		(2.656)		(2.644)		(2.654)		(2.644)
Respondent's age		0.206*		0.207*		0.200*		0.206*		0.197*
		(0.106)		(0.106)		(0.105)		(0.106)		(0.105)
Polygamous married (=1)		-2.922		-2.687		-3.282		-2.689		-3.349
		(7.511)		(7.482)		(7.588)		(7.526)		(7.519)
Widowed (=1)		-10.87**		-10.53**		-10.01**		-10.30**		-9.814**
		(4.651)		(4.646)		(4.601)		(4.635)		(4.632)
Separated/divorced (=1)		-7.002		-7.234		-6.899		-7.367		-7.272
		(4.577)		(4.582)		(4.583)		(4.619)		(4.601)
Not married (=1)		10.94		10.57		10.76		10.42		10.27
		(7.654)		(7.701)		(7.691)		(7.670)		(7.722)
Education (years completed)		-0.0756		-0.0133		-0.0401		-0.00479		-0.0205
		(0.367)		(0.367)		(0.365)		(0.366)		(0.365)
Land owned by household (acres)		-1.117***		-1.127***		-1.068***		-1.092***		-1.042***
		(0.356)		(0.354)		(0.350)		(0.352)		(0.353)
Land rented in last season (acres)		1.837		1.803		1.740		1.877		1.766
		(1.278)		(1.259)		(1.207)		(1.253)		(1.211)
Constant	42.04***	35.48***	40.66***	33.52***	39.29***	32.63***	40.59***	33.44***	39.54***	32.75***
	(1.678)	(6.116)	(1.389)	(6.076)	(1.447)	(6.082)	(1.432)	(6.107)	(1.592)	(6.141)
Observations	1,671	1,671	1,710	1,710	1,710	1,710	1,710	1,710	1,710	1,710
Number of farmers	593	593	600	600	600	600	600	600	600	600
Overall R-squared	0.00678	0.0324	0.00689	0.0312	0.0150	0.0381	0.00877	0.0327	0.0156	0.0383
Mean of dependent variable	44.96	44.96	44.96	44.96	44.96	44.96	44.96	44.96	44.96	44.96

Notes: Random-effects model. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data from the random rounds only. This table repeats estimation from Table 5 in main text without controls and with controls while displaying the coefficients on controls.

Table A.8: Impact of the within-village heterogeneity on farmers' individual contributions (fixed effects).

	Contribution to soil test as percentage of 2000 MK				
	(1)	(2)	(3)	(4)	(5)
Distance to plot selected (km)	-2.821*				
	(1.670)				
Same soil type from map (=1)		2.587**			
		(1.254)			
Similar soil from survey (=1)			4.099***		1.709
			(1.428)		(1.770)
Belongs to family/friend (=1)				3.554*	-0.738
				(1.957)	(2.579)
Similar soil from survey X Belongs to family/friend					6.557**
					(2.967)
Constant	43.58***	40.39***	39.55***	40.49***	39.70***
	(1.320)	(0.903)	(1.103)	(1.024)	(1.334)
Observations	1,671	1,710	1,710	1,710	1,710
R-squared	0.035	0.035	0.040	0.036	0.047
Number of farmers	593	600	600	600	600
Mean of dependent variable	44.96	44.96	44.96	44.96	44.96

Notes: Fixed-effects model. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Data from the random rounds only.

Table A.9: Impact of the within-village heterogeneity on farmers' individual contributions (by farmer type).

	Contribution to soil test as percentage of 2000 MK			
	(1)	(2)	(3)	(4)
Similar soil from survey (=1)	4.478***	5.050***	-0.0316	4.591**
	(1.317)	(1.745)	(0.987)	(1.927)
Respondent is female (=1)	4.410*	5.608**	0.526	4.076
	(2.644)	(2.710)	(0.763)	(2.815)
Respondent's age	0.200*	0.193*	-0.0409	0.191*
	(0.105)	(0.101)	(0.0290)	(0.106)
Polygamous married (=1)	-3.282	-7.996	-0.990	-8.361
	(7.588)	(7.454)	(0.655)	(8.293)
Widowed (=1)	-10.01**	-8.996**	1.651	-8.150
	(4.601)	(4.559)	(1.124)	(4.979)
Separated/divorced (=1)	-6.899	-4.222	3.497***	-7.167
	(4.583)	(4.855)	(1.057)	(4.975)
Not married (=1)	10.76	8.671	0.842	6.281
	(7.691)	(7.491)	(0.891)	(7.621)
Education (years completed)	-0.0401	0.305	-0.534***	0.598*
	(0.365)	(0.342)	(0.117)	(0.331)
Land owned by household (acres)	-1.068***	-0.414	0.456**	-0.709
	(0.350)	(0.683)	(0.193)	(0.703)
Land rented in last season (acres)	1.740	1.173	0.702	0.318
	(1.207)	(0.853)	(0.529)	(0.663)
Constant	32.63***	23.02***	18.79***	26.70***
	(6.082)	(5.954)	(1.901)	(6.203)
Observations	1,710	1,162	157	1,005
Number of farmers	600	406	54	352
Overall R-squared	0.0381	0.0395	0.176	0.0441

Notes: Random-effects model. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data from the random rounds only. Column (1) shows the entire sample (1,710 observations); column (2) limits the sample to farmers who change their contributions from round to round; columns (3) and (4) restrict the sample to farmers with average individual contribution below 350 MK or greater or equal 350 MK, respectively.

Table A.10: Impact of the within-village soil heterogeneity on village-round contributions.

	Mean of contributions as percentage of endowment				Coefficient of variation of contributions as percentage of endowment				Share of contributions below 350 MK			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Share of contributions to plots with dissimilar soil	-22.84				-0.268**				0.265**			
	(15.48)				(0.103)				(0.118)			
Average distance to sampled plots (km)		26.13***				-0.0373				-0.227***		
		(8.156)				(0.0876)				(0.0744)		
Number of village soil types			7.167***				-0.0318***				-0.0431***	
			(1.401)				(0.0118)				(0.0108)	
Variance of soil carbon from 5 plots				74.82***				0.335***				-0.0887
				(9.933)				(0.122)				(0.0926)
Share of female respondents	38.68***	22.54**	35.66***	12.02	-0.164	-0.158	-0.172	-0.293**	-0.207***	-0.0632	-0.182***	-0.162**
	(10.26)	(10.10)	(9.424)	(10.31)	(0.118)	(0.131)	(0.117)	(0.115)	(0.0718)	(0.0727)	(0.0682)	(0.0692)
Share of married respondents	54.95**	48.65**	43.12**	40.20*	0.318	0.174	0.182	0.167	-0.0826	0.00577	0.0533	0.0559
	(23.34)	(20.74)	(20.55)	(21.59)	(0.228)	(0.210)	(0.205)	(0.194)	(0.141)	(0.120)	(0.117)	(0.119)
Mean of respondents' age	-0.554*	-0.559*	-1.286***	-0.431	0.00447	0.00374	0.00681**	0.00461	0.0111***	0.0113***	0.0158***	0.0115***
	(0.321)	(0.315)	(0.315)	(0.313)	(0.00287)	(0.00295)	(0.00315)	(0.00312)	(0.00236)	(0.00249)	(0.00303)	(0.00242)
Standard deviation of respondents' age	2.139**	1.132	1.858**	1.947**	0.0111	0.00830	0.00715	0.00790	-0.0195***	-0.00979*	-0.0160***	-0.0159**
	(0.967)	(0.939)	(0.929)	(0.891)	(0.0120)	(0.0111)	(0.0113)	(0.0108)	(0.00597)	(0.00582)	(0.00565)	(0.00611)
Mean of respondents' education (years)	-0.762	-1.737	-3.995***	-0.134	0.00138	-0.000816	0.0113	0.00221	0.0275***	0.0368***	0.0485***	0.0296***
	(1.171)	(1.088)	(1.257)	(1.212)	(0.0122)	(0.0125)	(0.0139)	(0.0125)	(0.00963)	(0.0113)	(0.0129)	(0.0110)
Standard deviation of respondents' education	2.681	4.390	2.164	0.500	0.0621**	0.0422	0.0429*	0.0427	-7.07e-05	-0.0111	0.0104	0.0163
	(3.230)	(2.701)	(2.608)	(2.803)	(0.0266)	(0.0269)	(0.0254)	(0.0258)	(0.0233)	(0.0217)	(0.0192)	(0.0203)
Mean of respondents' land owned	6.131	3.030	8.553**	-4.668*	-0.128***	-0.137***	-0.155***	-0.184***	-0.106***	-0.0764***	-0.115***	-0.0828***
	(3.940)	(4.015)	(3.909)	(2.668)	(0.0314)	(0.0321)	(0.0331)	(0.0383)	(0.0298)	(0.0226)	(0.0288)	(0.0271)
Standard deviation of respondents' land owned	-5.773**	-2.639	-5.031**	-0.408	0.0986***	0.103***	0.106***	0.127***	0.0554***	0.0262*	0.0473***	0.0422**
	(2.479)	(2.619)	(2.480)	(1.709)	(0.0217)	(0.0220)	(0.0223)	(0.0249)	(0.0184)	(0.0137)	(0.0164)	(0.0168)
Mean of respondents' land rented	42.27***	48.75***	60.26***	19.01	-0.0460	-0.0351	-0.101	-0.139	-0.531***	-0.592***	-0.648***	-0.519***
	(15.45)	(13.32)	(14.41)	(14.14)	(0.0955)	(0.101)	(0.103)	(0.0988)	(0.0969)	(0.110)	(0.120)	(0.0999)
Standard deviation of respondents' land rented	-11.71**	-19.06***	-18.56***	-8.075	0.105***	0.0884**	0.102***	0.106***	0.126***	0.196***	0.178***	0.143***
	(5.255)	(4.550)	(4.522)	(4.869)	(0.0308)	(0.0373)	(0.0313)	(0.0315)	(0.0231)	(0.0389)	(0.0326)	(0.0286)
Constant	-33.58	-31.38	-12.10	-18.34	0.142	0.304	0.249	0.301	0.0927	0.0376	-0.106	-0.0551
	(35.44)	(30.96)	(34.23)	(35.48)	(0.453)	(0.431)	(0.424)	(0.391)	(0.239)	(0.199)	(0.215)	(0.231)
Observations	120	120	120	120	120	120	120	120	120	120	120	120
R-squared	0.342	0.378	0.429	0.503	0.356	0.332	0.354	0.371	0.366	0.404	0.399	0.326
Mean of dependent variable	46.66	46.66	46.66	46.66	0.63	0.63	0.63	0.63	0.15	0.15	0.15	0.15

Notes: Round fixed effects and village-level controls in all specifications include: share of female respondents, share of married respondents, mean and standard deviation of respondents' age, mean and standard deviation of respondents' education (years), mean and standard deviation of respondents' land owned and land rented. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Data from four rounds. This table repeats the estimation of Table 7 in main text, while displaying coefficients on the controls.

Table A.11: Correlation between number of farmers and contributions at the soil-type level.

	Village-round contributions		
	Mean	Coeff. variation	Share below 350 MK
	(1)	(2)	(3)
Number of farmers within soil type	0.199	0.00990*	-0.00335
	(0.441)	(0.00523)	(0.00399)
Share of female respondents	26.04***	-0.128	-0.176*
	(7.713)	(0.121)	(0.100)
Share of married respondents	35.51**	0.296	0.0769
	(15.96)	(0.196)	(0.137)
Mean of respondents' age	0.0337	0.00115	-0.00318
	(0.360)	(0.00455)	(0.00333)
Standard deviation of respondents' age	0.569	0.000447	-0.00412
	(0.441)	(0.00661)	(0.00628)
Mean of respondents' education (years)	0.174	0.00973	-0.00988
	(0.926)	(0.0119)	(0.0104)
Standard deviation of respondents' education	-3.852***	0.0763***	0.0373**
	(1.440)	(0.0205)	(0.0177)
Mean of respondents' land owned	-5.356	-0.114***	-0.00317
	(3.390)	(0.0386)	(0.0305)
Standard deviation of respondents' land owned	1.945	0.0837***	-0.000919
	(2.273)	(0.0274)	(0.0204)
Mean of respondents' land rented	1.943	-0.0311	-0.113*
	(6.011)	(0.0539)	(0.0575)
Standard deviation of respondents' land rented	-0.199	0.0654**	0.0208
	(2.990)	(0.0308)	(0.0268)
Constant	9.937	0.0749	0.347
	(24.13)	(0.408)	(0.277)
Observations	114	114	114
R-squared	0.251	0.385	0.154
Mean of dependent variable	46.21	0.62	0.15

Notes: This table presents the results of a regression analysis mapping contributions at the soil-type (within village-round) level onto the number of farmers within this soil-type. Data from all four rounds including only those observations where the soil-type matches the soil-type of the plot selected for soil testing and analysis. Round fixed effects and village-soil type-level controls in all specifications include: share of female respondents, share of married respondents, mean and standard deviation of respondents' age, mean and standard deviation of respondents' education (years), mean and standard deviation of respondents' land owned and land rented. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data from four rounds.

Table A.12: Impact of the within-village networks on village-round contributions.

	Village-round contributions		
	Mean	Coeff. variation	Share below 350 MK
	(1)	(2)	(3)
Village share of contributions towards plots of family/friends	-0.541	0.226**	0.0207
	(8.307)	(0.0890)	(0.0595)
Share of female respondents	37.23***	-0.123	-0.187**
	(10.93)	(0.117)	(0.0766)
Share of married respondents	42.71*	0.431*	0.0751
	(22.55)	(0.244)	(0.145)
Mean of respondents' age	-0.613*	0.00533*	0.0118***
	(0.337)	(0.00309)	(0.00253)
Standard deviation of respondents' age	1.798*	0.0156	-0.0150**
	(0.981)	(0.0120)	(0.00640)
Mean of respondents' education (years)	-1.064	0.0108	0.0318***
	(1.192)	(0.0133)	(0.0121)
Standard deviation of respondents' education	1.376	0.0381	0.0145
	(2.834)	(0.0238)	(0.0198)
Mean of respondents' land owned	5.036	-0.117***	-0.0923***
	(4.081)	(0.0305)	(0.0271)
Standard deviation of respondents' land owned	-5.075**	0.0907***	0.0463***
	(2.527)	(0.0203)	(0.0165)
Mean of respondents' land rented	43.81***	-0.0317	-0.549***
	(16.06)	(0.101)	(0.112)
Standard deviation of respondents' land rented	-13.83**	0.117***	0.153***
	(5.329)	(0.0345)	(0.0325)
Bidding round = 2	3.127	0.00955	0.0281
	(3.743)	(0.0399)	(0.0270)
Bidding round = 3	7.175*	-0.000366	0.0175
	(3.725)	(0.0364)	(0.0267)
Bidding round = 4	10.23**	-0.0212	-0.00175
	(4.024)	(0.0389)	(0.0266)
Constant	-19.72	-0.289	-0.105
	(40.97)	(0.498)	(0.293)
Observations	120	120	120
R-squared	0.326	0.371	0.322
Mean of dependent variable	46.66	0.63	0.15

Notes: Round fixed effects and village-level controls in all specifications include: share of female respondents, share of married respondents, mean and standard deviation of respondents' age, mean and standard deviation of respondents' education (years), mean and standard deviation of respondents' land owned and land rented. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data from four rounds.